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Modeling of Behavioral Changes in Agent-Based Simulations

Bridging the gap between social and computer science by operationalizing psychological processes

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Abstract

This dissertation contributes to the field of pedestrian dynamics. Pedestrian dynamics tries to better understand crowd behavior to make gatherings safer. In particular, one wants to avoid crowd disasters like the one at the Love Parade festival in Germany, 2010, with 21 dead or at the Hajj with hundreds of casualties in several years. Pedestrian dynamics researchers carry out experiments and simulate large crowds and pedestrian streams. Current crowd simulation models mostly focus on physically correct simulations but neglect psychological aspects which affect crowd behavior. This dissertation describes my efforts to model behavioral changes in agent-based simulations and how I try to bridge the gap between computer science and social sciences to get accurate crowd simulation results.

In Part I of this work, I conduct an exhaustive literature research on current modeling approaches and psychological aspects. I distill three important concepts from the broad research field of psychology that must be integrated into state-of-the-art simulations: perception, cognition and behavior. In Part II of this dissertation, I implement these aspects in an established open-source simulation tool. I base my modeling efforts on latest psychological findings. I implement the findings as reusable psychology layer which can easily be integrated into other crowd simulation tools to be beneficial for the whole research community. My modeling effort is supported by an own experiment with 58 participants in which I document human behavior in a specific safety-relevant scenario. In the experiment, I extract quantitative and qualitative data for the model refinement and validation. I use three real-world scenarios to show that my approach is able to reenact a wide range of human behavior which can be observed in reality.

My modeling approach is easy to understand and reusable. It aims to better connect natural and life sciences because knowledge from both disciplines is necessary to simulate and understand crowd behavior. My approach also provides clear guidelines to operationalize observed human behavior for future simulations with the three sequential phases perception, cognition and a selection of suitable behaviors.

Keywords: computer science, psychology, pedestrian dynamics, modeling, experiment, humans, behavioral changes
With: 97 figures, 18 tables, 14 listings, 221 references

Zusammenfassung

Diese Arbeit trägt zum Forschungsgebiet der Fußgängerdynamik (engl. Pedestrian Dynamics) bei. Pedestrian Dynamics versucht das Verhalten von Menschenmengen besser zu verstehen und so Veranstaltungen sicherer zu machen. Im Besonderen gilt es, Katastrophen zu verhindern wie bei der Loveparade 2010 in Deutschland mit 21 Toten oder wiederholt bei der jährlichen Haddsch. Forscher auf dem Gebiet der Fußgängerdynamik versuchen das Verständnis durch zwei Teilbereiche zu vertiefen: Experimente mit Menschen und der Simulation von Menschenmengen. Dabei fokussieren sich die gegenwärtigen Simulationsmodelle überwiegend auf eine physikalisch korrekte Simulation. Jedoch werden bei der Simulation psychologische Aspekte vernachlässigt, welche sich auf das Verhalten von Menschenmengen auswirken können. Aus diesem Grund widmet sich diese Arbeit diesem Missstand. Die Dissertation beschreibt die Modellierung von menschlichen Verhaltensänderungen für agentenbasierte Fußgängersimulationen.

Der erste Teil dieser Arbeit widmet sich einer umfassenden Literaturübersicht zu aktuellen Modellierungsansätzen und psychologischen Aspekten, welche menschliche Verhaltensänderungen beeinflussen können. Aus dem breiten Forschungsgebiet der Psychologie arbeite ich drei essentielle Konzepte heraus, welche in State-of-the-Art-Simulationen integriert werden müssen: Perzeption, Kognition und Verhalten. Im zweiten Teil dieser Arbeit implementiere ich diese drei wesentlichen Konzepte in einem etablierten Open-Source-Fußgängersimulator. Dabei fußt meine Implementierung auf neuestem psychologischen Wissen. Der Fokus meiner Arbeit liegt in der Schaffung einer wiederverwendbaren Architektur, welche sich auch einfach in eine Vielzahl weiterer Fußgängersimulatoren integrieren lässt. Aus diesem Grund kapsle ich meine Implementierung als wiederverwendbare Psychologieschicht. Dadurch ist meine Modellierung und Implementierung für die gesamte Forschungsgemeinschaft nützlich. Meine Modellierung wird unterstützt durch ein eigenes Fußgängerexperiment mit 58 Teilnehmern. Ich nutze die neu geschaffene Psychologieschicht, um drei reale Situationen als Simulationen nachzustellen. Die erfolgreiche Anwendung zeigt, dass mein Ansatz in der Lage ist, ein breites Spektrum von menschlichen Verhaltensänderungen korrekt und realitätsnah abzubilden.

Mein Modellierungsansatz ist einfach zu verstehen und vor allem wiederverwendbar. Mein Ziel ist es Natur- und Sozialwissenschaften besser zu verbinden, da Wissen aus beiden Bereichen notwendig ist, um das Verhalten von Menschenmengen zu verstehen und korrekt zu simulieren. Mein Ansatz liefert klare Leitlinien für Modellierer, um menschliches Verhalten systematisch für Simulationen zu operationalisieren. Diese Leitlinien sind durch Perzeption, Kognition und einem Verhaltensrepertoire gegeben.

Themenbereiche: Informatik, Psychologie, Fußgängerdynamik, Modellierung, Experiment, Menschen, Verhaltensänderungen
Mit: 97 Abbildungen, 18 Tabellen, 14 Listings, 221 Quellen

Acknowledgment

My role as writer and principal researcher of this dissertation is only one part of the game. There are many other people in the background which influenced my thoughts and supported this work.

I would like to thank Hans-Joachim Bungartz for supervising this dissertation from the university side. This should be not taken for granted because my research group is hosted at the Munich University of Applied Sciences. But, it is Hans' diverse interest in many topics which makes this collaboration possible and it is a great platform to exchange ideas and to share knowledge. Hans, you are available at any time of the day — and also all night long — willing to give feedback. Therefore, thank you very much!

I would like to thank Gerta Köster for building up the pedestrian dynamics research group at the Munich University of Applied Sciences and proofreading this work. You write time-consuming research proposals, ask for funding and provide valuable feedback in discussions. This ensures that researchers with different backgrounds (computer science, mathematics, mechanical engineering and also psychology) can work on interesting research questions across disciplines. This interdisciplinarity promotes understanding. Former members of the research group (Michael Seitz, Isabella von Sivers and Felix Dietrich) helped to build up the research group from which the current generation of researchers benefits.

I would like to thank the current members of the research group: Benedikt Zönnchen, Daniel Lehmberg, Marion Gödel, Stefan Schuhbäck, Christina Mayr and Simon Rahn. We had a lot of fun in our daily work, when visiting conferences or also in our leisure time. Keep up the good work.

A special thanks to John Drury for inviting and hosting me at the School of Psychology (University of Sussex) in 2019. The collaboration and discussion with John and members of his research group "Crowds & Identities" helped enormously to operationalize observed behavior and mold it into a reusable computer model. The research stay helped to bridge computer science and psychology and is a starting point to get more reliable pedestrian and crowd simulations.

A special thanks to two brave proofreaders: Benedikt Zönnchen and Simone "Zitrone" Jehl. And of course, thank you to my family. It is good to have you!

"Everything should be made as simple as possible, but not simpler."

Attributed to Albert Einstein
(O'Toole 2011)

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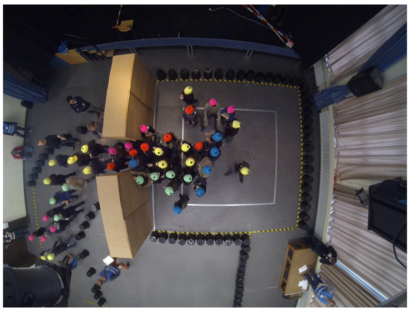
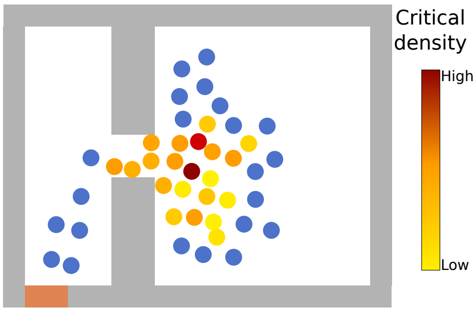
Chapter 1 Introduction

This dissertation contributes to the field of pedestrian dynamics. More concretely to the simulation of pedestrians and how their movement and behavior evolves over time. The term pedestrian dynamics encompasses a wide range of research activities to better understand crowds. On the one hand, it covers experiments in closed and open spaces, with single pedestrians or large crowds, experiments under laboratory or field conditions. These experiments analyze pedestrian and collective phenomena like clogging at bottlenecks, lane formation in counterflow scenarios or evacuation times for different motivation levels, cooperative or competitive, and exit widths. On the other hand, pedestrian dynamics covers the modeling of pedestrians and crowds to carry out simulations, see Fig. 1.1. These simulations can help to identify risks in the planning phase of crowd events or to make buildings safer to ensure certain evacuation times.



(a) An evacuation experiment conducted by Krüchten et al. 2016.



(b) A simulation of the experiment setup with the Vadere simulation framework conducted by myself.

Figure 1.1: (a) An evacuation experiment where participants wore colored hats and **(b)** a subsequent simulation to identify critical high densities (video footage of the experiment can be found at: `https://doi.org/10.34735/ped.2014.1`).

1.1 Motivation: Why we need pedestrian dynamics models

My personal motivation for my research activities is to better understand crowds and to avoid risks wherever crowds gather. Pedestrian and crowd simulations are a useful support for evacuation planning and safety concepts for crowd events and provide valuable insights into pedestrian streams and waiting systems. Also, in times of global pandemics, like COVID-19, simulations can help to test the effectiveness of social distancing. For instance, how likely is it to get infected in a supermarket? I think that it is the planning phase where computer simulations help most. Simulations identify critical densities, maybe, caused by architectural shortcomings of the venue. Such shortcomings led to injuries and even casualties in the past. For instance, 21 people died at the Love Parade music festival in Duisburg, Germany, in 2010 when visitor waves crushed together because a tunnel was used as an entry and an exit simultaneously as revealed by (Helbing and Mukerji 2012), see Fig. 1.2. Also several casualties were reported at the Hajj (Challenger et al. 2009, p. 187). Lastly, 769 fatalities were documented after a stampede at the Hajj in Mina, 2015 (Alqahtani et al. 2016, Tab. 1, p. 7–9). These are only a few examples of many more crowd disasters. Simulations allow to test hypotheses without harming people and can give decision makers clear guidelines where critical densities occur and if certain scenarios can threaten life and limb.

Figure 1.2: Festivalgoers in severe danger when trying to escape from being crushed at the Love Parade in Germany 2010. A tunnel was used as entry and exit simultaneously. The organizers overestimated the capacity of the tunnel which could have been revealed by simulations in the planning phase of the event. 21 Festivalgoers were killed during the crush (photo: Wiffers 2010).

1.2 Challenges in simulating pedestrian dynamics

My understanding of modeling and simulation starts by observing the real world. Then, a mathematical and algorithmic model of the real world is derived. In a further step, this model must be implemented as computer program to be able to carry out simulations with varying parameter sets to test “what-if scenarios”. Each step must be carefully verified to minimize introduced errors. Fig. 1.3 summarizes my understanding of the modeling and simulation pipeline.

In the last few years, we have seen an increasing interest in the research of pedestrian dynamics as the upsurge in publications shows, see Fig. 1.4.

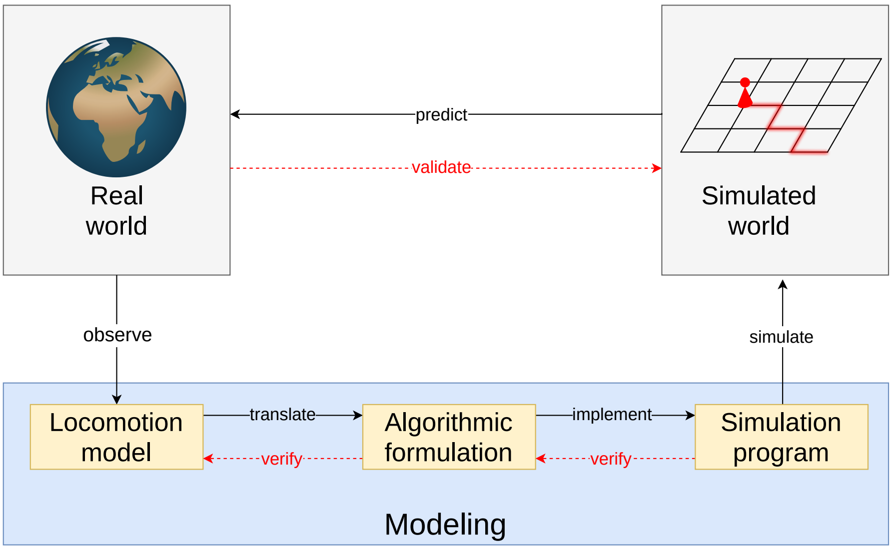
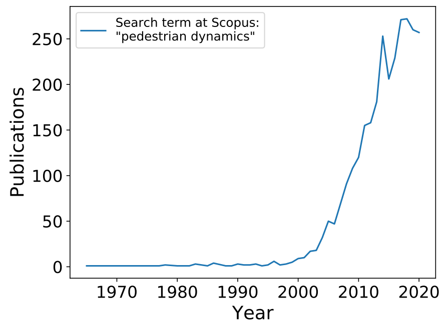
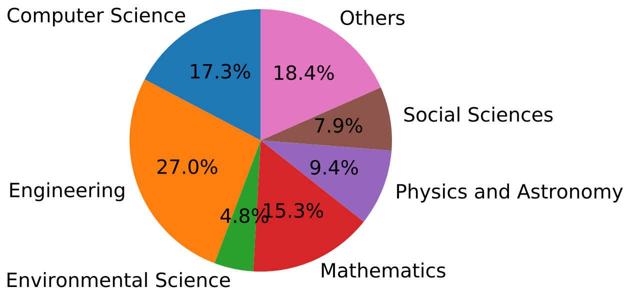


Figure 1.3: My understanding of modeling and simulation: from the real world to simulations. First, observe the real world. Then, derive a mathematical locomotion model, translate it into an algorithmic formulation which is implemented as computer program. Lastly, carry out simulations to get new insights into pedestrian streams. Each step must be carefully verified to obtain accurate simulation results (own graphic but globe icon from Free SVG 2020).



(a) An increasing number of publications since the year 2000.



(b) Different disciplines contribute to "pedestrian dynamics".

Figure 1.4: The upsurge in scientific publications demonstrates an increasing interest in the research of "pedestrian dynamics". The publications were collected in the Scopus citation database for peer-reviewed literature (Elsevier 2020b). The search revealed 2880 publications and was carried out at Dec 11, 2020.

Attracting researchers from different disciplines is a great benefit for the pedestrian dynamics research community. It allows to tackle problems from different perspectives and to derive creative solutions. In my eyes, this comes with three major challenges: empirical challenges, modeling challenges and interdisciplinary challenges.

The starting point of each modeling effort should be observations of the real world. But, to obtain reliable data from observations is a challenging task. While field observations allow a great number of (unbiased) participants in a natural environment it is difficult to get experiment approvals because of ethical and data privacy concerns. On the other hand, data privacy concerns are easier to handle in experiments under laboratory conditions with a smaller number of participants. Laboratory experiments face other challenges. An experimenter needs a representative sample of the whole population to draw valid and general conclusions. The participants must not be biased or primed in any sense which is hard to achieve if an experiment consists of multiple repeating runs. Experimenters should collect quantitative and qualitative data. Especially, for natural scientists it is hard to design a valid questionnaire to collect qualitative data because these researchers are usually not trained to detect social or psychological issues which could prime participants in an undesired way. Collecting quantitative data requires expensive equipment like cameras. Usually, filming an experiment calls for multiple cameras and also "backup" cameras for unforeseen incidents. This raises financial and logistic problems. For instance, an experiment requires a sufficient number of experiment assistants to guide the participants and to operate cameras and further experiment equipment. Extracting pedestrian trajectories can also be a time-consuming task when done manually. These aspects show that conducting an experiment to obtain reliable data involves a plethora of challenges.

But also modeling imposes several challenges. The umbrella terms modeling or simulations are typical examples for "pars pro toto" (a part describes the whole) as stated by (Bungartz et al. 2014, p. 2). The word modeling or simulation hides the whole pipeline behind it. Simulations are the third pillar beside theoretical analyses and experiments to promote understanding. As Bungartz et al., I also think that "simulations complement analyses and experiments but they do not replace them". Simulations are a useful tool to get new insights in different domains where theoretical analyses are hardly possible or not covered by experiments (e. g., the evacuation of a whole city). But, obtaining an accurate model is also challenging. One must find a correct mathematical description of an observed phenomenon. For instance, how can behavioral changes in a crowd be described mathematically? Often, it is hard to describe pedestrian and crowd behavior mathematically. In a further step, the mathematical model must be translated into an algorithm, a finite sequence of instructions which can be understood by computers. Each step involves pitfalls and is a source for possible mistakes. Examples are a missed parameter in the mathematical model, numerical problems and instabilities when discretizing the continuous world, or programming errors when implementing the algorithm in a programming language. Most notably, a model should be easy to understand for a wide range of researchers and also for decision makers. They must be able to trust the simulation output. Therefore, a model should not contain too many parameters. A scientifically valid model must be "falsifiable" as postulated by (Popper 1935).

As shown in Fig. 1.5, pedestrian dynamics involves different research disciplines and goals. On the one hand, different perspectives offer a great possibility to solve problems in an uncommon and creative way. On the other hand, working interdisciplinary imposes great challenges. Each discipline uses different terminology, and usually background knowledge is missing to completely understand the research approaches and methodologies of a different discipline. It takes time to acquire knowledge and methodologies from different disciplines and usually time is limited when there is pressure to succeed. Therefore, interdisciplinary work is often met with skepticism.

Figure 1.5: Pedestrian dynamics is an interdisciplinary research topic (own graphic but inspired by: Büchele 2014, p. 2).

1.3 Goals and research question

Nowadays, pedestrian and crowd simulations are widely used to test and legitimate construction plans or crowd management plans for large-scale events (Mauri 2019). Therefore, these simulations must be accurate and reliable. In the last few years, a plethora of physically inspired (loco) motion models arose which have been extended continuously. Their key assumption is the "homo oeconomicus": simulated pedestrians — agents — search for the shortest path from a starting to a destination point. All these locomotion models include destinations, or targets, which attract agents while obstacles and other agents repel agents. But, especially, in high-density situations such simulations often end in dead lock situations were agents do not move anymore while in the real-world we can observe that pedestrians maintain flow. Agents stick to one behavior throughout the simulation.

During my research, I identified the following gap: modeling physically correct pedestrian streams is not sufficient to reenact real-world observations. To make pedestrian simulations more reliable, new falsifiable models are needed that respect psychological processes of humans. Additionally, such new models should be easy to understand so that they are beneficial for an interdisciplinary research community of physicists, mathematicians, computer scientists, sociologists, psychologists and others as well as practitioners.

To address the scientific gap, I pose the following research question:

Research question

How can changes in human behavior be operationalized for simulations?

From the research question, I derive following four objectives for this dissertation:

- To research and document individual and social human behaviors and triggers that lead to behavioral changes.
- To develop a reusable model that allows behavioral changes of agents.
- To implement the model to proof that it can be realized and is not yet another theoretical model.
- To validate the implementation against real-world data to show the usefulness of the model for future predictions.

1.4 Structure of this work

To answer the research question adequately, I base my work on three pillars:

1. A literature research: I conducted an exhaustive literature research about state-of-the-art approaches to model pedestrian streams and existing approaches to model behavioral changes.
2. An own experiment for a specific safety-relevant scenario: I carefully conducted an own experiment to observe and document human behavior and behavioral changes quantitatively and qualitatively.
3. A close cooperation with a social psychology research group: As computer scientist, I visited the social psychology professor Dr. John Drury and his research group. I attended his course "Psychology of Crowds and Collective Actions" and I worked closely together with his research group to manifest a strong psychological perspective in the new model. As computer scientist and modeler, the goal is to boil down all input into a reusable, falsifiable and accurate model.

In Fig. 1.6, I cluster the research question into modeling, implementation and testing tasks. The division into sub-tasks and goals respectively helps to work in a structured way. To solve all these problems, I apply different research methods which are depicted as the lowest layer in Fig. 1.6.

This dissertation describes my efforts to model behavioral changes in agent-based simulations and how I try to bridge the gap between social and computer sciences. The dissertation is subdivided into two parts:

- Part I
  - Sec. 2 scrutinizes current computer models for pedestrian dynamics, existing pedestrian stream simulators and useful validation techniques to test my own model.

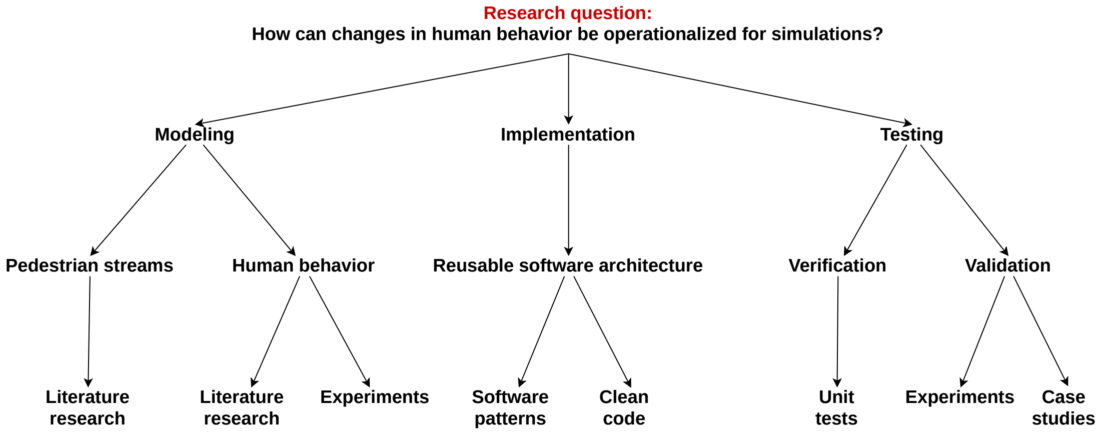


Figure 1.6: The research question, derived tasks and sub-tasks and applied research methods.

  - Sec. 3 introduces the psychological perspective in the context of crowd dynamics and I distill which aspects influence human decision-making and can have an effect on pedestrian streams.
  - Sec. 4 adds concepts from social psychology in the context of crowd dynamics and how humans behave as social beings.

- Part II
  - Sec. 5 outlines the requirements of my model for behavioral changes of agents and the technological foundation I base my implementation on.
  - Sec. 6 describes how I incorporate all findings from the locomotion and psychological perspective into a reusable psychology layer — with sub-layers perception, cognition and behavior — which is implemented in the Vadere simulation framework.
  - Sec. 7 demonstrates the versatility of my modeling approach by validating simulations against three different real-world scenarios.

The target audience of this dissertation are primarily computer scientists, but researchers from life sciences, like psychologists, should be able to read this dissertation easily. I put special effort in making the content easy to understand. Wherever possible, I try to make complex topics, e. g. mathematical formulas, understandable through pictures. Additionally, I make code listings as simple as possible by rigorously applying a clean-code paradigm. Due to the interdisciplinary nature of the work, the literature review in Part I is somewhat more extensive, as two areas need to be addressed (locomotion models and psychological aspects).

1.5 Infrastructure and tools

I would like to give recognition to some great software tools which hugely supported my research work. Most of the software tools are open source or at least free and I would like to thank all software authors for their continuous effort. Tab. 1.1 summarizes the software tools which I primarily used along with the version numbers:

- This document is typeset with LaTeX using TeXstudio and TeXLive 2017. JabRef is used for the citation management. UML diagrams and flowcharts are created with draw.io.
- I use the IntelliJ IDEA Community Edition for Java programming tasks when working on a pedestrian simulator in Sec. 6. The PyCharm Community Edition is used for Python-related programming tasks. Python is primarily used for data analysis tasks in Sec. 7 in connection with the matplotlib library for plotting tasks. Python is also used as "glue logic" to trigger continuous integration tasks consistently.
- Kubuntu 18.04 is used as operating system which is based on the GNU/Linux software basis.
- All my code contributions are under version control using Git and are publicly available on https://gitlab.lrz.de/vadere/vadere under the GNU Lesser General Public License to promote knowledge transfer.

Software	Version	Link
LaTeX (pdfTeX)	3.14159265-2.6	https://www.latex-project.org/
TeXstudio	2.12.6	https://www.texstudio.org/
TeXLive	2017	https://www.tug.org/texlive/
JabRef	5.0.0	https://www.jabref.org/
draw.io	13.0.3	https://www.diagrams.net/
OpenJDK Java	11.0.9.1	https://openjdk.java.net/
IntelliJ IDEA	2019.01	https://www.jetbrains.com/idea/
PyCharm	2018.1.4	https://www.jetbrains.com/pycharm/
Python	3.6.9	https://www.python.org/
Git	2.17.1	https://www.git-scm.com/
Kubuntu	18.04	https://kubuntu.org/

Table 1.1: The primary software which was used for this dissertation.

Part I

State of the Art

In the following three sections, I provide an overview of the state-of-the-art literature to answer my central research question: how can changes in human behavior be operationalized for simulations to get better insights into pedestrian dynamics? So far, pedestrian streams were mostly inspected and modeled by natural scientists like physicists, mathematicians or computer scientists with a strong focus on physically correct locomotion models to navigate agents through virtual environments. But, until now, the social science perspective has mostly been neglected when modeling pedestrian streams. For instance, why do pedestrians change their behavior and how do these changes look like? This is where social sciences can help to promote understanding of pedestrian dynamics. Therefore, I would like to shed light on both topics in my literature overview: state-of-the art techniques to model pedestrian streams from the typical natural science perspective but also include the psychology perspective to explain why pedestrians change their behavior. The following table Tab. 1.2 represents my "search grid" which I used to collect useful literature from several scientific citation databases like Google Scholar, Datenbank-Infosystem (DBIS), ACM Digital Library, IEEE Xplore, arXiv, Science Direct, Scopus, Springer Link and World Scientific (Google 2020; Universität Regensburg 2020; Association for Computing Machinery 2020; Institute of Electrical and Electronics Engineers 2020; Cornell University 2020; Elsevier 2020a; Elsevier 2020b; Springer Nature Switzerland 2020; World Scientific Publishing 2020). The search grid allows to conduct a systematic, transparent and reproducible literature research.

	Search terms	
AND / OR	physics	mathematics
	informatics	computer science
	modeling	operationalization
	simulation	computer simulation
	pedestrian	crowd
	dynamics	streams
	human	individual
	stationary	dynamic
	dense	high density
	scenarios	bottleneck
	counterflow	bidirectional flow
	agents	agent-based
	locomotion	movement
	validation	verification
	psychology	social psychology
	collective actions	social norms
	social identity theory	self-categorization theory
	emergency	situation
	perception	sensation
	cognition	behavior
	behavioral changes	sociology
	AND / OR	

Table 1.2: A "search grid" for the research question visualizing important keywords for investigating the topic during the literature research. The logical AND / OR in the first column and the last row signals how to combine these search terms during the literature research. Sophisticated search engines let the user combine several search terms explicitly by logical operators. For instance, "physics AND simulation AND pedestrian" or "(physics OR mathematics) AND simulation AND pedestrian".

Chapter

2 Simulations of pedestrian dynamics

As outlined in the introduction in Sec. 1, my goal is to integrate psychological processes into pedestrian simulation tools. Therefore, I scrutinize existing computer models for pedestrian dynamics and their realization in simulation tools. I answer the following questions: what are relevant modeling approaches to maneuver agents through virtual environments? Which models already include insights from a psychological perspective? Which open-source and commercial simulators exist using these modeling concepts and are candidates to implement my own findings? How can simulations be validated?

2.1 Different perspectives on pedestrian streams

As visualized in Fig. 1.5 and described by Kleinmeier, Zönnchen, et al. 2019, p. 2, pedestrian dynamics is an active and versatile research field that attracts scientists from different disciplines. Biologists, sociologists, psychologists, physicists, computer scientists, engineers, mathematicians and others share a common goal: to enhance the understanding of crowd behavior. Each researcher strives for new insights by using different techniques. For instance, biologists and psychologists observe and analyze human behavior that affects pedestrian movement and describe their findings verbally. Physicists and mathematicians mold the observed behavior into equations. And computer scientists transform the mathematical equations into computer models to carry out simulations.

This interdisciplinary research character means that different perspectives on pedestrian streams exist. Similar to physics, we can look at pedestrian streams from a macro-, meso- and microscopic perspective. While the macroscopic can be perceived by the naked eye[1] and reveals large-scale units, the microscopic requires special measurement instruments which yield small-scale units. In physics, also the term "mesoscopic" gained popularity in the last few years, especially, in biomaterials science or mesoscopic physics "which indicates physics on the scale between nanometers and micrometers where quantum phenomena appear to interfere with macroscopic, [...] principles" (Nakatsuji 2013).

In the context of pedestrian dynamics, a typical measure on the macroscopic level is the density in number of people per area or the pedestrian flow in number of people per second per unit length (Adrian et al. 2019, p. 5). Whereas, on microscopic level a typical measure is the speed of individuals, the step length of pedestrians or the fundamental

[1] Merriam-Webster. (n.d.). Macroscopic. In Merriam-Webster.com dictionary. Retrieved June 16, 2020, from https://www.merriam-webster.com/dictionary/macroscopic.

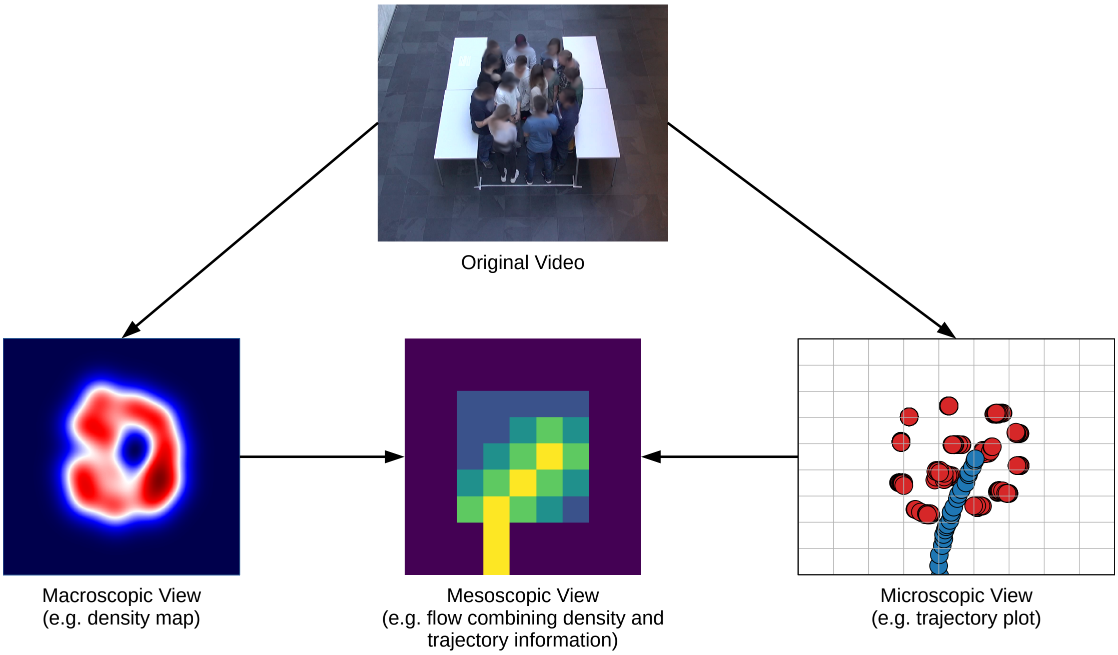


Figure 2.1: Typical measures on macro- and microscopic scale based on real-world video footage: the density in number of people per area (macroscopic, left) and the position of individuals over time combined as trajectory (microscopic, right). The mesoscopic scale (middle) in pedestrian dynamics can be derived by combining macroscopic and microscopic measures. The original video footage shows a waiting crowd which is crossed by one walking person denoted as blue circular shape in the density map and in the trajectory plot.

diagrams which link density and speed (see Fig. 2.2 as an example). Fig. 2.1 visualizes two typical measures for the macroscopic and the microscopic view. The mesoscopic view combines measures from the macro- and the microscopic level. In pedestrian dynamics, it highly depends on the application which view is useful because all views have advantages and disadvantages. For instance, for practitioners like crowd managers, the macroscopic view with the density measure is a useful tool to decide if an event location is overcrowded or not. Crowd managers are not interested in the distinct stepping behavior of individual visitors on the microscopic level. In contrast, the microscopic level is interesting for researchers who investigate queuing and bottleneck scenarios for example. These researchers need to know how the step length of individuals evolves over time to reveal clogging situations.

2.2 Pedestrian stream models for locomotion

The previous Sec. 2.1 showed that different perspectives on pedestrian streams exist: the macro-, meso- and microscopic view. Depending on the application one view has advantages over the other. As we will see in the next sections, crowd modelers have implemented numerous models and extensions to existing models. Before reviewing them, it makes sense to group them together in rough classes. One possibility is to use the existing scales: macroscopic, mesoscopic and microscopic. Inspired by physics, I classify modeling approaches for pedestrian dynamics as macroscopic, mesoscopic or

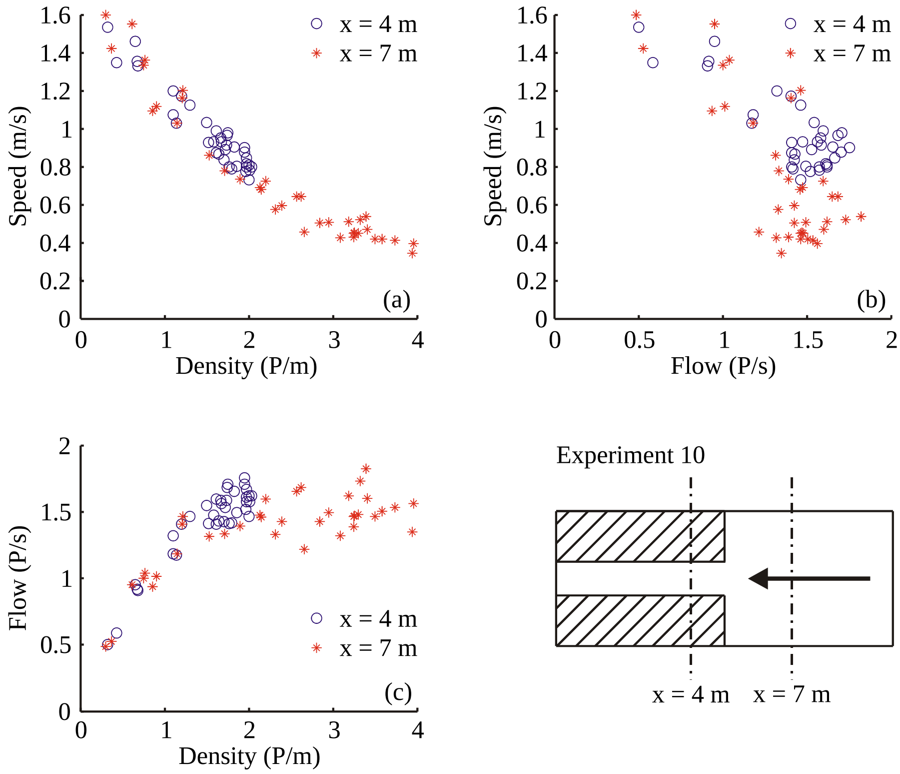


Figure 2.2: Example of three fundamental diagrams published in Daamen 2004, p. 83 which are based on a narrow bottleneck experiment. Fundamental diagrams are a graphical tool to study traffic flow. The two dimensional graphs visualize the basic relationship flow = speed × density which can be expressed by speed-density, speed-flow and flow-density graphs. Fundamental diagrams allow researchers to study specific traffic scenarios. A typical observation of the fundamental diagram is a decreasing speed with increasing density (Weidmann 1993, p. 62).

microscopic. While macroscopic modeling approaches cover large-scale areas like whole cities, microscopic approaches cover small-scale areas like single buildings. Finally, the mesoscopic approaches cover medium-scale areas, see Tab. 2.1.

Modeling approach	**Application**	**Examples**
Macroscopic	Large-scale areas	Cities
Mesoscopic	Medium-scale areas	Urban districts
Microscopic	Small-scale areas	Single buildings (e. g. stadiums, airports)

Table 2.1: My classification of pedestrian dynamic models into macro-, meso- and microscopic modeling approaches and their possible usage.

Of course, the scale is subjective and open to debate. For instance, one can also use a macroscopic model to simulate pedestrian motion inside a single room of several square meters. On the other hand, it is also possible to use microscopic models for simulating large-scale areas. While in the first case the resulting quantity (e. g. density) may be too imprecise, in the second case the computational time may be very long.

So far, I have used an analogy from physics to describe pedestrian streams as macro-, meso- or microscopic. For me, it is a useful approach to define the scale first (that is, what should be modeled or simulated) and then look for possible techniques for this scale. Crowd modelers have picked up these ideas and developed and implemented models accordingly. In the next three sections, I review existing modeling approaches which fall into macroscopic, mesoscopic or microscopic category. In 2019, 41 researchers from natural sciences and psychology addressed the lack of clear definitions in the pedestrian dynamics community. The researchers agreed on terms that are frequently used in research on human crowds like agent or models (micro-, meso- and microscopic) and published their work as glossary (Adrian et al. 2019).

In the pedestrian dynamics context, macro-, meso- and microscopic also define the level of detail which is used to describe pedestrian streams. While microscopic approaches model pedestrians in great detail, distinguish individuals and their interactions, macroscopic approaches model pedestrian streams as a whole and neglect individuals (Kormanová 2013, p. 2). Mesoscopic approaches are set between microscopic and macroscopic. Pedestrians are considered as individuals but their behavior is described as aggregated relationship (Adrian et al. 2019). In the following three sections, I will provide an overview of existing macro-, meso- and microscopic pedestrian stream models and I will review if these models are suitable to use them as basis for modeling behavioral changes. I include screenshots of simulation results from the original model publications to give the interested reader a better insight in the capabilities of the presented models. The timeline in Fig. 2.3 visualizes the chronology of influential locomotion models within the pedestrian dynamics community.

Figure 2.3: A timeline of selected locomotion models including their original authors. The locomotion models are grouped by their type: macro-, meso- or microscopic.

Beside the scale, there are other classifications of pedestrian dynamics. For instance, Zheng, Zhong, and Liu 2009 divided models into cellular automata, lattice gas models, social force models, fluid-dynamic models, agent-based models, game-theoretic models and “approaches based on experiments with animals”. In contrast, Seitz 2016, p. 39, classifies models by what is being modeled rather than by real-world analogies used for them. In his dissertation, Seitz focused only on microscopic pedestrian models where he distinguishes **(1)** cellular automata where rules defines the transition from one state to the next **(2)** velocity-based models where the velocity of agents is described by first-order ordinary differential equations and **(3)** force-based models which are described mathematically by second-order ordinary differential equations.

The terms “agent” and “pedestrian”

Note: in the current pedestrian dynamics modeling literature, the term “agent” is frequently used. Throughout this work, **I use the term “agent” to describe a simulated person while reserving the words “pedestrian”, “human” and “crowd” for the real-world counterpart.** While macroscopic locomotion models neglect individual pedestrians as we will see in the following, microscopic locomotion models try to mimic individual pedestrians as closely as possible. In these models, agents are equipped with a wide range of attributes like height, step length or a preferred speed, which is also called free-flow velocity. When individuals are subject of modeling often the term agent-based model is used.

2.2.1 Macroscopic locomotion models

Model definition and overview As Adrian et al. 2019, p. 8, define in their glossary, macroscopic locomotion models “do not distinguish individuals. The system dynamics are described using aggregate quantities, such as densities or flows.” Macroscopic pedestrian models are the oldest model types and were introduced in 1955 by Lighthill and Whitham to describe traffic flow in general. Later, this model was refined to describe pedestrian dynamics. Macroscopic pedestrian models have in common that they are based on physical laws and are expressed by differential equations which usually describe density evolution over time. Pedestrian crowds are seen as “thinking fluid” (Tordeux, Lämmel, et al. 2018, p. 129). Due to their close relationship to physics, macroscopic models were mostly introduced by mathematicians or physicists who are primarily faced with ordinary or partial differential equations as part of their education. Newer approaches avoid differential equations and use the definition of flow and density to describe pedestrian motion on a macroscopic level. These newer approaches are rather descriptive models than explaining models. That is, these descriptive models are applied to video footage for example to analyze pedestrian movement. But, they are not used to carry out simulations in the end. In the following section, I will describe three macroscopic models in more detail in chronological order. I cluster them into Lighthill-Whitham-Richards models — the first macroscopic models for traffic flow —, hydrodynamic models and first-order flow models.

Model examples

Lighthill-Whitham-Richards models (mathematics background) As Bungartz et al. 2014, p. 151 describe, if one would take a picture of road traffic from bird's eye view in the night with long exposure time, one would notice that cars flow like a viscous liquid. Fig. 2.4 visualizes the idea to "liquidize" the discrete road traffic into a continuous flow.

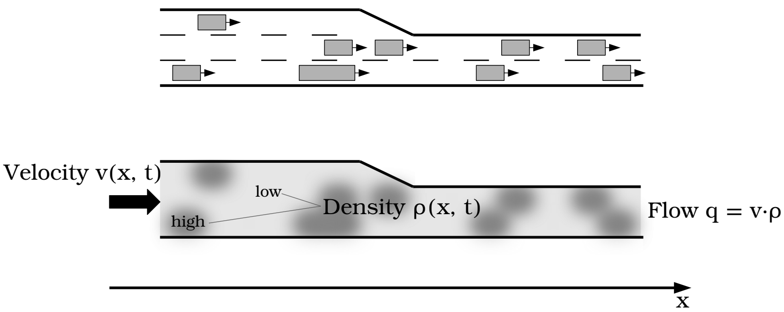


Figure 2.4: Liquidization of discrete road traffic into a continuous flow (own graphic but inspired by: Bungartz et al. 2014, p. 151).

Back in 1955, the mathematicians Lighthill and Whitham picked up this "liquidization" idea and proposed a macroscopic model to describe an unidirectional flow of vehicles. One year later, in 1956, Richards independently proposed a similar model for describing traffic flow. Both models rely on the basic relationship flow $=$ speed $\times$ density, which the authors described as: "[the] fundamental hypothesis of the theory is that at any point of the road the flow q (vehicles per hour) is a function of the concentration k (vehicles per mile)" (Lighthill and Whitham 1955, p. 319). Later, both models referenced as Lighthill-Whitham-Richards (LWR) model. The LWR model assumes that the discrete flow of vehicles can be approximated by a continuous flow which is expressed by a hyperbolic differential equation Eq. 2.6.

Usually, (partial) differential equations are not self-explanatory and it requires some unpacking to get behind their intuition. One central idea for describing physical phenomena is the conservation law which states in a broader sense that the total quantity of a measurable does not change over time in an isolated system. This also holds true for a traffic system with pedestrians: on an isolated road section $[a, b]$ without entries or exits, no pedestrian should be lost. By integrating the density $\rho(x, t)$ which depends on the location x and the time t, one can derive the number of road users $n(t)$ in section $[a, b]$, Eq. 2.1:

$$n(t) = \int_a^b \rho(x, t)\, dx \tag{2.1}$$

Applying the derivative to both sides yields the change in the numbers of road users at time t, Eq. 2.2:

$$\frac{\partial}{\partial t} n(t) = \int_a^b \frac{\partial}{\partial t} \rho(x, t)\, dx \tag{2.2}$$

Additionally, also the flow q yields the change in the numbers of road users at time t:

$$\frac{\partial}{\partial t}n(t) = f(a,t) - f(b,t) = -\int_a^b \frac{\partial}{\partial x}q(x,t)\,dx \tag{2.3}$$

Combining Eq. 2.2 and 2.3 results in:

$$\int_a^b \frac{\partial}{\partial t}\rho(x,t) + \frac{\partial}{\partial x}q(x,t)\,dx = 0. \tag{2.4}$$

It is also known that this holds true for every time instant t and therefore, it is plausible to drop the integral and to denote that the flow q depends on the density ρ, which leads to the continuity equation where Lighthill and Whitham drew upon, Eq. 2.5.

$$\frac{\partial}{\partial t}\rho(x,t) + \frac{\partial}{\partial x}q(\rho(x,t)) = 0. \tag{2.5}$$

Eq. 2.5 captures the initial idea of the LWR model. Lighthill and Whitham and Richards added additional factors and a diffusion term denoted by second derivatives, see Eq. 2.6 (Lighthill and Whitham 1955, p. 344). Both extensions shall make the model more accurate. The second derivative with respect to time accounts for the fact that road users have a reaction time before they can adapt their velocity. The second derivative with respect to location models that speeding-up or slowing-down cannot happen instantaneously.

$$\frac{\partial q}{\partial t} + c\frac{\partial q}{\partial x} + T\frac{\partial^2 q}{\partial t^2} - D\frac{\partial^2 q}{\partial x^2} = 0 \tag{2.6}$$

Lighthill-Whitham-Richards model examples Colombo and Rosini presented their macroscopic pedestrian model in 2005 with the goal of providing an analytically treatable framework to analyze situations caused by a "sharp increase in the density" (Colombo and Rosini 2005, p. 1555). They describe such situations with the fuzzy word "panic". The authors base their model on the Lighthill-Whitham-Richards (LWR) model which was originally intended for vehicular traffic. Colombo and Rosini motivate their choice for the LWR model because it only has two assumptions:

1. Conservation: the total number of pedestrians is constant.
2. Speed law: the speed v is a function of the density ρ.

Colombo and Rosini assume a typical flow which is depicted in Fig. 2.5, but they extended Eq. 2.6 by their own assumptions. They modify the speed law by introducing what they call "characteristic density". In contrast to the classic LWR model, these special density allows pedestrians to move even if the density grows above the maximum density R in Fig. 2.5. In this case, modeled pedestrians "feel" overcompressed but they can still move. Analytical difficulties bound the authors to consider only one-dimensional cases which makes the model unsuitable for real-world applications.

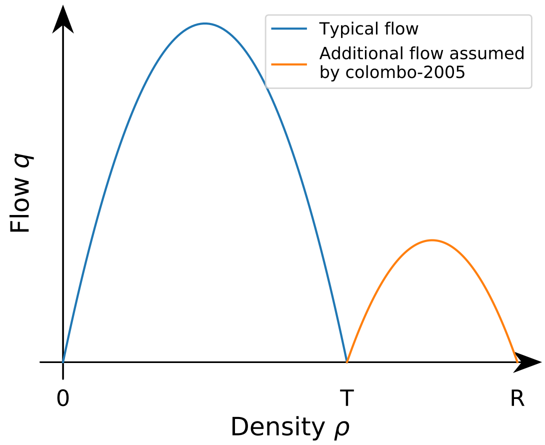


Figure 2.5: A typical flow-density diagram. First, the flow q increases with increasing density ρ. After reaching a density threshold T, the flow decreases until it completely stops at a density value R. Colombo and Rosini assumed for their Lighthill-Whitham-Richards-based model that pedestrians can still move even if a critical density T is reached.

Hydrodynamic models (physics background) In hydrodynamic models, individual pedestrians are aggregated to a larger swarm and these models assume that such a swarm moves like compressed fluids or gasses. These modeling approaches try to capture the density and speed changes in time accurately by using differential equations. Hydrodynamic models are based on the Boltzmann equation or the Navier-Stokes equations. Typically, following types of liquids or flows are distinguished: **(1)** Viscous and inviscid fluids. Viscosity describes the “toughness” of liquids. While gases are inviscid, fluids are more viscous. **(2)** Laminar and turbulent flows. In the former, the single streams of a liquid do not easily blend in the course of the flow. In the latter, the different streams easily blend resulting in turbulences. **(3)** Compressible and incompressible liquids. While gases are a typical example of compressible flows, liquids stand for incompressible flows.

One example to describe the spatial and temporal dispersion of laminar, viscous flows of incompressible fluids is the Navier-Stokes equation (named after the French physicist Claude-Louis Navier and the Irish physicist George Stokes). Navier and Stokes describe the conservation of momentum and mass by connecting three physical quantities: **(1)** The velocity field $u(x, y, t)$, **(2)** The pressure $p(x, y, t)$ and **(3)** The density $\rho(x, y, t)$. In the incompressible case the density ρ is assumed constant. Then, the Navier-Stokes equation describes the flow as following:

$$\frac{\partial}{\partial t}u + (u \cdot \nabla)u = -\nabla p + \frac{1}{\text{Re}}\triangle u + g, \tag{2.7}$$

where $\operatorname{div} u = 0$, $\text{Re} \in \mathbb{R}$ represents the dimensionless Reynolds number, ∇ is the gradient operator, $\triangle$ the Laplace operator and $g = (g_x, g_y)^{\text{T}}$ denotes the sum of external forces like gravitation. By using the velocity u and the viscosity v, Eq. 2.7 can be reformulated as (Bungartz et al. 2014, p. 358–360):

$$0 = \frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} \tag{2.8}$$

To be able to solve Eq. 2.8, initial values for the velocity have to be provided as well as boundary values at the boundary of the domain for all times.

Hydrodynamic model examples In 1974, Henderson was the first who used a hydrodynamic model to describe human crowd motion (Helbing 1992, p. 391). Henderson assumed a conservation of energy in his model which is quite unrealistic because simulated agents usually enter and leave the simulated area which could lead to an unbalanced situation. For example, more agents enter the simulation area than leaving the area. In contrast, Helbing's fluid-dynamic model for the movement does not enforce the conservation of energy. The differential equations in Helbing 1992 describe the change of density over time which is influenced by four effects (Helbing 1992, p. 393–395):

1. The tendency of pedestrians to reach their intended velocity.
2. The interactions between pedestrians.
3. The changes of pedestrian types when turning left or right (at crossings).
4. The density gain or loss per time unit.

Helbing's model is able to produce walking lanes and traffic jams.

Another hydrodynamic model was introduced by Hughes in 2000. Hughes assumes that crowd motion follows well-defined rules of behavior. Therefore, Hughes embedded his observations on crowd movement into three hypotheses. The original formulation of the hypotheses are (Hughes 2000, p. 368):

1. "It states that the speed, f, at which pedestrians walk is determined solely by the surrounding pedestrian density and the behavioural characteristics of the pedestrians, [...]"
2. "It states that pedestrians have a common sense of the task (called potential) that they face to reach their common destination such that any two individuals at different locations having the same potential would see no advantage to either in changing places. There is no perceived advantage to a pedestrian of moving along a line of constant potential. Thus the motion of any pedestrian is in the direction perpendicular to the potential, [...]"
3. "It states that pedestrians seek to minimize their (accurately) estimated travel time, but temper this behaviour to avoid extremely high densities."

From these hypotheses Hughes derived highly non-linear differential equations to replicate the path and density of a crowd. Hughes conceives that the "greatest difficulty in applying this formulation involves the appropriate choice of boundary conditions to match the psychological state of the pedestrians" (Hughes 2000, p. 370). The boundary conditions are very important because they have a huge effect on the observed flow pattern of the model.

First-order flow models (civil/transportation engineering background) In contrast to hydrodynamic models, first-order flow models try to replicate fundamental diagrams for pedestrians, e. g. the speed-density relationship. They use the velocity (directed) or the speed (undirected) as central element — which is expressed as first derivative of the time-dependent position $x(t)$ of an object and gives the model its name. For these models, the pedestrian trajectories must be known in advance. It is a data-driven approach to describe and analyze existing pedestrian streams instead of simulating unknown geometries. Thus, first-order flow models are rather descriptive models than explaining models.

First-order flow model examples In 2004, Daamen developed a first-order flow model in her dissertation and published it as Daamen, Hoogendoorn, and Bovy 2005. From known trajectories of N pedestrians, she derives a function $N(x,t)$ which represents the number of pedestrians passing a cross-section x from an arbitrary starting moment t. Using this information, she calculates the flow q at the cross section x during the time period from t_1 to t_2, see Eq. 2.9:

$$\text{Flow } q(x, t_1 \text{ to } t_2) = \frac{N(x,t_2) - N(x,t_1)}{t_2 - t_1} \tag{2.9}$$

At each time t when a pedestrian passes the cross section x, the speed of this pedestrian is measured as well. Using this information, the density at x at time t can be derived by the basic relationship flow $=$ speed $\times$ density $\Leftrightarrow$ density $= \frac{\text{flow}}{\text{speed}}$, see Eq. 2.10:

$$\text{Density } k(x,t) = \frac{q(x,t)}{v(x,t)}, \tag{2.10}$$

where $v(x,t)$ denotes the speed of the pedestrian at cross section x at time t.

Conclusions on macroscopic locomotion models Macroscopic pedestrian stream models do not replicate each pedestrian individually. Instead, macroscopic models try to capture the motion of all aggregated pedestrians as a whole, e. g. in form of a density evolution over time. This approach makes macroscopic models computational fast for large numbers of simulated agents compared to microscopic models where each pedestrian is modeled individually. My goal is to model behavioral changes of simulated agents. Wijermans 2011 revealed that collective behavior stems from actions of individuals. Thus, the lack of individualism makes macroscopic models unsuitable to integrate my findings from a conceptional point of view. How should psychological effects be integrated into such macroscopic pedestrian models? By adding additional terms into its mathematical definition?

Furthermore, macroscopic models often result in differential equations to describe the flow or density evolution over time. Differential equations are thoroughly studied in mathematics and well-grounded theories exist to solve them numerically, e. g. by finite differences or finite element methods. But, applying these techniques is not trivial, especially, for non-mathematicians like engineers and practitioners. On the other hand, differential equations are usually not easily understood by an interdisciplinary research community ranging from psychologists to physicists (see Fig. 1.5, p. 5). With my modeling of behavioral changes, I am addressing an interdisciplinary research community to promote understanding across discipline boundaries. In summary, macroscopic models do not suit my purpose from a conceptual point of view but also not from an implementation point of view.

2.2.2 Mesoscopic/Multi-scale locomotion models

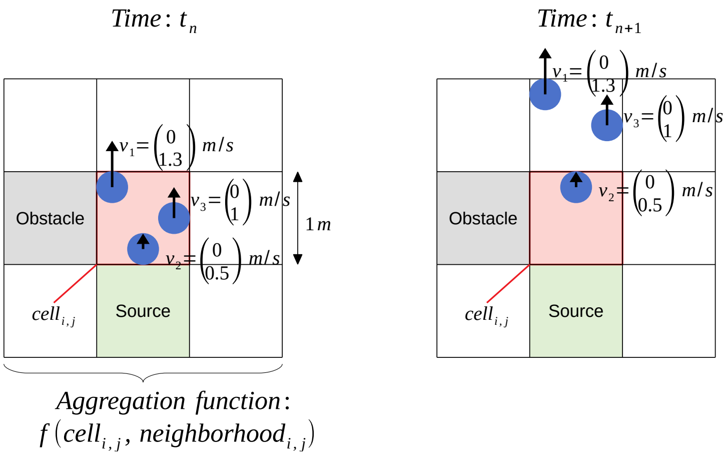
Model definition and overview A modern definition of mesoscopic models in the context of pedestrian dynamics can be found in Adrian et al. 2019, p. 8. The authors set mesoscopic models “in between microscopic and macroscopic models. It does not aim to describe aspects, such as the motion and behaviour, of each individual, but only certain aspects.” Another key aspect is that agents are considered as individuals but their motion is described as aggregated relationship. Usually, models of this type divide the simulation area into rectangular or hexagonal cells which can be occupied by multiple agents simultaneously, see Fig. 2.6, p. 22. This differs from cellular automata on microscopic level (see Sec. 2.2.3), where one cell can be occupied by only one agent. Then, a function aggregates all agents together and defines the next cell for the agents based on individual properties of the agents. One of these properties could be the preferred velocity of an agent. Existing mesoscopic models mostly differ in the aggregation function and how they move agents over to the next cell or region. Some authors also use graphs instead of cells.

Other research disciplines like hydrodynamics often refer to the term “multi-scale modeling” when combining macroscopic and microscopic approaches. The goal of such “multi-scale approaches” is to compute large-scale areas efficiently but also maintain microscopic accuracy for subareas of the whole simulation area. The interested reader is referred to Cristiani, Piccoli, and Tosin 2014, a book which is dedicated to multi-scale modeling of pedestrian dynamics. From a modeling perspective, the great challenge for multi-scale models is how information are exchanged between the macroscopic and the microscopic layer. For instance, how is a density information from the macroscopic perspective converted into individual agent positions for microscopic calculations and vice versa.

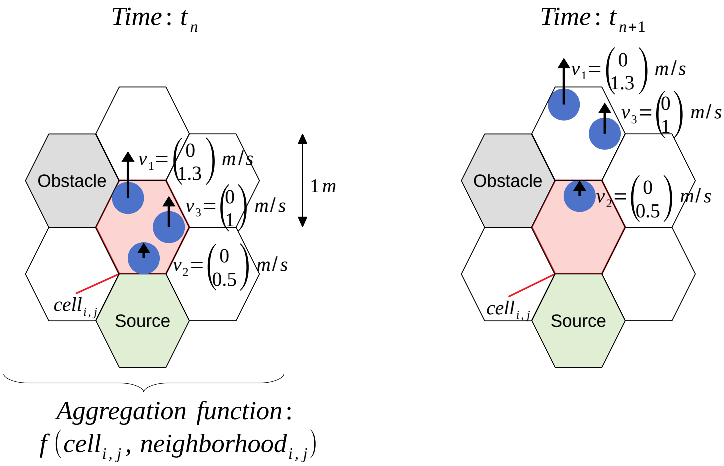
Model examples

teknomo-2008, Fig. 2.3 (civil/transportation engineering) The transportation engineers Teknomo and Gerilla claimed that in “the analysis, however, such microscopic [pedestrian] model will always be aggregated into either mesoscopic level or macroscopic level” (Teknomo and Gerilla 2008, p. 3). Of course, this claim is disputable because when analyzing the clogging at bottlenecks microscopic quantities like step lengths are of great interest and they should not be aggregated to macroscopic quantities. Nevertheless, Teknomo and Gerilla propose a mesoscopic pedestrian model with following properties.

The authors use a grid with square cells to cover the simulation area. In contrast to microscopic cellular automata, one cell can be occupied by multiple agents. They choose a cell size between $1\,\mathrm{m}\times1\,\mathrm{m}$ and $3\,\mathrm{m}\times3\,\mathrm{m}$. It must be large enough, so that agents cannot skip single cells because of too high speeds. When choosing the cell size $0.5\,\mathrm{m}\times0.5\,\mathrm{m}$ and restricting the cell density to one pedestrian per cell one ends up with a cellular automaton described by Schadschneider 2001 or Kretz, Grünebohm, and Schreckenberg 2006 (cellular automata are described in more detail in Sec. 2.2.3, p. 33).



(a) A rectangular grid structure used by mesoscopic models.



(b) A hexagonal grid structure used by mesoscopic models.

Figure 2.6: Most mesoscopic locomotion models divide the simulation area into rectangular or hexagonal cells which can be occupied by multiple agents simultaneously. Then, an aggregation function aggregates all agents together and defines the next cell for the agents based on the cell neighborhood and individual properties of the agents. One of these properties could be the preferred velocity of an agent. Some models use rectangular cells where different neighborhood definitions exist (Moore or von Neumann neighborhood). Other models use triangular or hexagonal cells with an unitary neighborhood definition.

To move agents from cell to cell, the authors use the three matrices N_D, N_L and N_Q. N_D represents the pedestrian count in each cell. N_L describes the simulation layout where zero entries represent obstacles, one entries represent free cells and high values represent target cells. N_Q provides information to navigate agents to the target similar to a floor field (see Sec. 2.2.3, p. 32) which encodes the geodetic distance to a target (Burstedde et al. 2001). The authors combine these matrices by using the entry-wise product denoted by $\bullet$ and normalize the resulting matrix by dividing each matrix element by the maximum matrix value. This normalization is denoted by $||\cdot||_{\max}$:

$$N_p = ||N_D \bullet N_L \bullet N_Q||_{\max} \tag{2.11}$$

Then, an agent's new position is calculated by using the old position x_t and the movement direction $v_t = \arg\max N_p$ and combining them to $x_{t+1} = x_t + v_t$. The flowchart in Fig. 2.7 visualizes the update scheme for each agent in each simulation step.

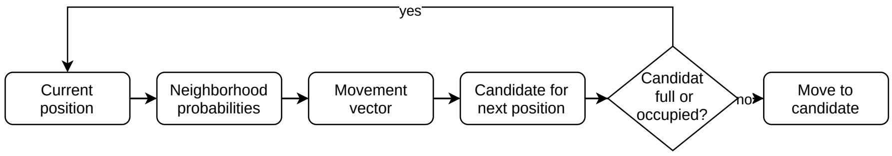
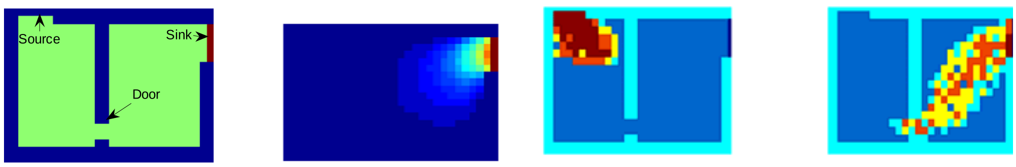


Figure 2.7: Flowchart of the agent movement in each simulation step defined by Teknomo and Gerilla 2008, p. 6. The neighborhood probabilities take three influences into account: **(1)** The layout of the area, e. g., if the neighbor cell is an obstacle or a source. **(2)** The speed-density relationship in the neighbor cells (the speed and density information are derived from existing fundamental diagrams). **(3)** The attraction of the neighbor cell to the pedestrian target. This information encodes the direction and travel time to the target.

The authors use two parameters to adapt the model to specific simulation areas. The first parameter represents the target attraction in "sink" cells. The second parameter influences the density matrix N_D which affects the probability to enter a cell. This second parameter is a flow-related quantity — like for all mesoscopic models — expressed as speed-density function. The authors used their model to carry out five simulation runs based on a rectangular floor plan with either one or two rooms, compare Fig. 2.8.



(a) Left: the constructed layout matrix, right: the constructed navigation matrix (image: Teknomo and Gerilla 2008, p. 10)

(b) The density evolution in a one-door scenario (image: Teknomo and Gerilla 2008, p. 11).

Figure 2.8: Teknomo and Gerilla simulated a $20\,\mathrm{m} \times 30\,\mathrm{m}$ room which is separated by a single door. Their model yields a density evolution over time for 50 agents.

bellomo-2012, Fig. 2.3 (mathematics) The mathematicians Bellomo, Piccoli, and Tosin critically survey existing macro-, meso- and microscopic modeling approaches for pedestrian dynamics. They state that macroscopic approaches model pedestrians as continuum under assumption of the conservation law but neglect the behaviors and motions of individuals. That is, in all macroscopic models pedestrians are seen as reactive particles instead of active participants. Therefore, the authors' goal is to express the pedestrian's "active ability to express a strategy" as mathematical structure which is not centered around the Newtonian concepts and the passive behavior of inertia matter (Bellomo, Piccoli, and Tosin 2012, p. 8). The authors suggest that one-to-one interaction between pedestrians can be best described by microscopic quantities like positions instead of macroscopic quantities like density. Their model is based on three concepts: desired velocity of pedestrians, an interaction neighborhood and an interaction kernel which reflects interactions between two agents (Bellomo, Piccoli, and Tosin 2012, p. 16).

They translate the interaction kernel into an Eulerian model consisting of a partial differential equation[2]. In contrast to other models presented in this mesoscopic overview, this model is continuous in space and allows to directly obtain agent positions (Bellomo, Piccoli, and Tosin 2012, p. 18). The model is based on the microscopic agent positions $\{X_t^i\}_{i=1}^N$ for N agents at time t. From the microscopic positions, the authors derive a probability distribution which is described by Eq. 2.12.

$$\mu_t(E) = Prob(X_t^i \in E), \quad E \subseteq \mathbb{R}^d \text{measurable} \tag{2.12}$$

The probability distribution $\mu_t(E)$ describes the positions of all pedestrians i at time t. Then, the actual pedestrian motion is described by the time derivative $\dot{X}_t^i$ in Eq. 2.13:

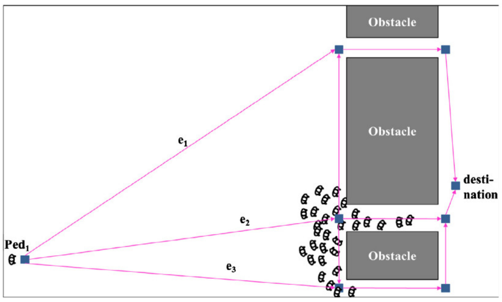
$$\dot{X}_t^i = v_{\text{des}}(X_t^i) + \sum_{X_t^j \in S_R(X_t^i)} F(X_t^i, X_t^j; N\mu_t(B_r(X_t^j))), \quad i = 1, ..., N \tag{2.13}$$

where $v_{\text{des}}(X_t^i)$ is the desired velocity field which drives each agent to its destination, $S_R(X_t^i)$ is the interaction neighborhood of the ith pedestrian and F represents the interaction kernel. The interaction kernel describes how a pedestrian adapts the desired velocity due to binary interaction with pedestrians in the considered neighborhood. The neighborhood is described by the ball $B_r(X_t^j)$ which is centered at X_t^j with radius $r > 0$. Bellomo, Piccoli, and Tosin provide only the bare model without an implementation. Therefore, also any simulation results and validations are missing.

kneidl-2013, Fig. 2.3 (computer science) Kneidl, Hartmann, and Borrmann's goal is to efficiently compute large simulation areas. To this end, the authors use two approaches to route agents through the simulation area: **(1)** Graphs, which are computational efficient, are used for long-range navigation decisions of agents (see Fig. 2.9, p. 25). **(2)** A cellular automaton (see Sec. 2.2.3, p. 33) is used for subareas of the simulation area to get accurate microscopic quantities like queuing behavior. The cellular automaton helps to dynamically update edges of the graph in the course of the simulation. For instance, a congested corridor in the cellular automaton (that is, the agent's average speed over a certain time is close to zero) lets delete a vertex in the graph and make this route inaccessible for agents. On the other hand, the graph helps to identify which cells of the cellular automaton must be updated in a simulation step. The authors demonstrated their hybrid model by simulating an urban area in Munich with $731\,\text{m} \times 545\,\text{m}$ with 2400 agents.

laemmel-2014, Fig. 2.3 (geoinformatics/transportation engineering)
Lämmel, Seyfried, and Steffen combine a mesoscopic queuing model and a microscopic pedestrian model to preserve the quantities flow, density and speed across model boundaries (Lämmel, Seyfried, and Steffen 2014). Their goal is to simulate hundreds of thousands agents inside New York's Grand Central Terminal train station, see Fig. 2.10. The authors use a mesoscopic model which is based on a graph with links and nodes inspired by Simon, Esser, and Nagel 1999. The links in the graph have a flow capacity and a storage capacity. A link cannot release more "vehicles or pedestrians per second" than

[2] In fluid dynamics, an Eulerian model uses a fixed reference grid to track the particle motion at a very specific location instead of the Lagrangian model where the observer follows a particle along its way.



(a) A constructed navigation graph with edges e_i (image: Kneidl, Hartmann, and Borrmann 2013, p. 6).

(b) A simulation result with 2400 agents in an urban area (image: Kneidl, Hartmann, and Borrmann 2013, p. 12).

Figure 2.9: Kneidl, Hartmann, and Borrmann simulated an urban area of $731\,\mathrm{m} \times 545\,\mathrm{m}$ with 2400 agents.

the flow capacity. Additionally, "once a link is full, vehicles that want to enter the link need to wait. This leads to queue spill-back through the network" (Simon, Esser, and Nagel 1999, p. 941). For the pedestrian movement on the links, the authors use a microscopic obstacle velocity model called ORCA (optimal reciprocal collision avoidance). Within the microscopic model, neighboring agents are taken into account by considering a visibility radius.

The flow-related parameters of their model are the link length l, the free-flow travel time τ , the flow capacity q, and the storage capacity c. The author's parameter definition is given by Eq. 2.14 to Eq. 2.16.

$$\text{Free-flow travel time } \tau = l/v_0, \tag{2.14}$$

where v_0 describes the properties of a link (e. g. plane, stair or ramp).

$$\text{Flow capacity } q = w \cdot 1.2 \frac{1}{\mathrm{m\,s}}, \tag{2.15}$$

where w describes the minimum bottleneck width to a link and the authors assume a width-dependent scaling factor of 1.2.

$$\text{Storage capacity } c = A \cdot \rho_{\text{max}}, \tag{2.16}$$

where A describes the area and ρ_{max} the maximum density.

The authors divide the simulation area into regions where each region can have its own simulation model, either the macroscopic queuing model or the microscopic ORCA model. The assignment of a model to a simulation area is static and does not change in the course of a simulation. The complexity of this model arises at the transition zones of two models. Agents are gradually transferred between the two models to preserve the fundamental features of density and flow. This hybrid model was able to simulate 750,000 agents within 2:43 hours (Lämmel, Seyfried, and Steffen 2014, p. 10) with two profound disadvantages from a microscopic perspective: all agents on one link move on a single line which results in implausible trajectories. And bidirectional flows are not simulated correctly because oncoming agents do not interact properly with each other.

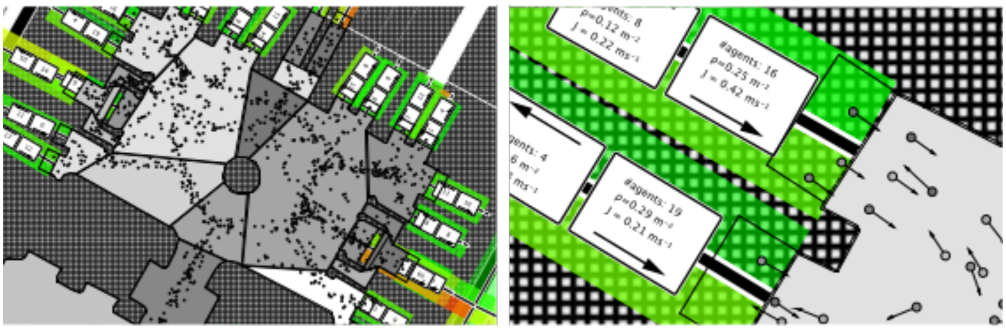


Figure 2.10: Simulation results by Lämmel, Seyfried, and Steffen 2014 of New York's Grand Central Terminal train station. The left visualization depicts that edges of the underlying graph data structure end in a departure hall. The departure hall is covered by a microscopic pedestrian model. The right visualization stresses the transition zones between both modeling approaches (image: Lämmel, Seyfried, and Steffen 2014, p. 10).

biedermann-2016, Fig. 2.3 (modeling/simulation) The goal of Biedermann et al. is to simulate agent movement with mixed spatial resolutions at a large event site. They model the "Back to the Woods" festival, an annual open air festival with approximately 5000 visitors which takes place in Garching, Germany. Arriving pedestrians are modeled by a macroscopic approach. The authors assume that the pedestrians arrive with bus shuttles at the event with multiple bus stops along that way. Biedermann et al. set up a generalized Dynamic Min-Cost Flow Problem (Ford and Fulkerson 1958) to minimize the waiting time for passengers at the bus stops. For their optimization, they use a graph-based approach where vertices are bus stops and edges are travel times between bus stops. The macroscopic model controls the inflow into the event site. For the simulation of the event site, two microscopic models are used. Large areas on the event site are modeled as cellular automaton and smaller areas with complex geometry like entrances are modeled on micro scale using a social force model. Their model also works with transition zones like Lämmel, Seyfried, and Steffen 2014 but here two microscopic models are coupled. The authors use a cellular automaton which is computational more efficient than the social force model for larger areas. One of the authors' simulation results is visualized in Fig. 2.11. The authors have not validated the simulation so far, but they identified the density in certain areas and trajectories as possible quantities for validation.

tordeux-2018, Fig. 2.3 (civil engineering) In 2018, Tordeux, Lämmel, et al. introduced another mesoscopic pedestrian model where pedestrians are considered as individuals and their movement is described by a density-flow relationship. The authors use a grid with hexagonal cells to get an unambiguous neighborhood definition. Thus, the model is discrete in space but continuous in time. One hexagonal cell can be occupied by multiple agents. The authors categorize pedestrians into classes c, for instance slower and faster ones. Then, they define a "jump rate" $b^{(c)}$ for each category c which depends on the current flow J and the direction D to the intended target cell i.

$$b^{(c)}(n,i) = \frac{K}{n} J^{(c)}(n,n_i) \cdot D^{(c)}(h_i, J^{(c)}(n,n_i)), \tag{2.17}$$

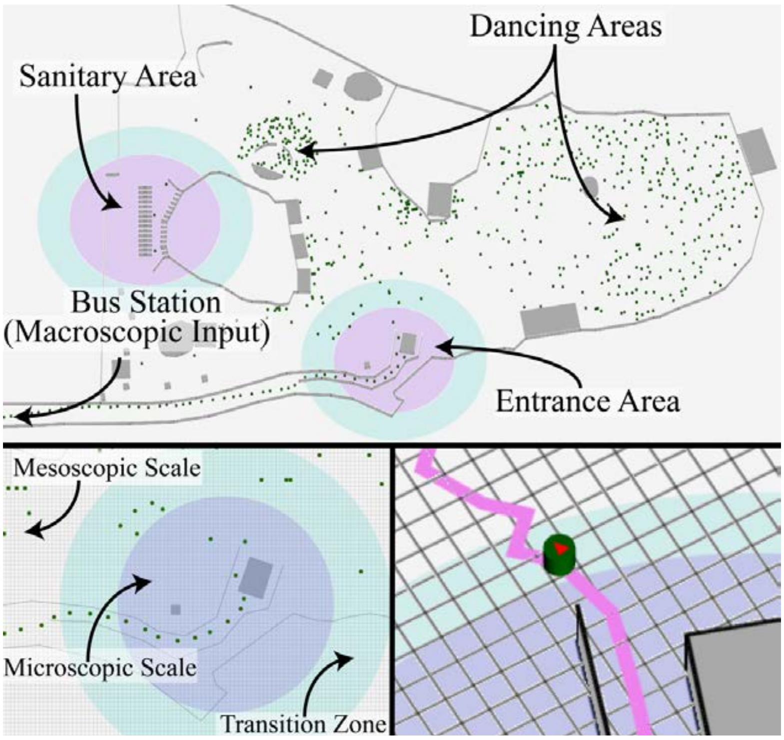


Figure 2.11: Biedermann et al. simulate a large music festival with different spatial resolutions. While pedestrian movement in open areas is modeled by a cellular automaton, the movement in more complex areas is covered by the social force model (image: Biedermann et al. 2016, p. 11).

where $J^{(c)}(n, n_i)$ describes the flow of n agents of the source hexagon to the target hexagon i (which already contains n_i agents) and the directional factor $D^{(c)}(h_i, J^{(c)}(n, n_i)$ where h_i represents the direction to the target hexagon. The movement direction D is set to maximize the flow, but also a static floor field (see Sec. 2.2.3, p. 32) could be used to derive D. Obstacles are represented as cells with a flow of $J = 0$. Based on Eq. 2.17, the total jump rate to a target cell i is expressed as sum

$$b(n, i) = \sum_{m=1}^{n} b^{c_m}(n, i) \tag{2.18}$$

The authors use existing density-flow fundamental diagrams to derive the flow function J depending on the scenario type. As scenario types, they consider uni- and multi-directional scenarios. In each simulation step, the flow from cell to cell is calculated based on the defined jump rate.

The authors applied their model to a rectangular walkway with $25\,\mathrm{m}$ by $50\,\mathrm{m}$ with up to 8000 agents. They used periodic boundary conditions. Agents who leave the scenario on one end reenter the scenario on the other end. The model yields congestion in uni-directional flows when obstacles are introduced and lane formation in bi-directional flows, see Fig. 2.12. Additionally, the authors validated the model against empirical data from bottleneck, counter- and cross-flow experiments with closed and open geometries. The travel and egress time is used as validation data. Lastly, the authors applied the model to a large real-world scenario where approximately 300,000 individuals are evacuated from an urban area of $4\,\mathrm{km}$ by $7\,\mathrm{km}$ which is typically too large for microscopic models.

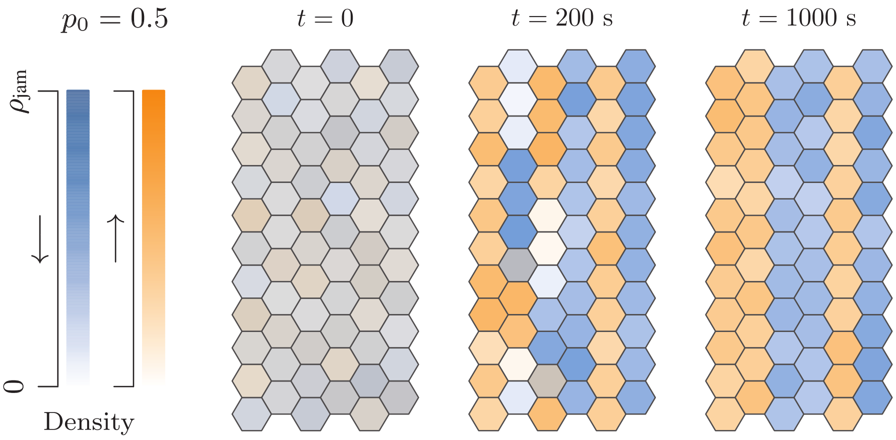


Figure 2.12: The model by Tordeux, Lämmel, et al. is able to reproduce lane formation as emergent behavior which is visualized in their density snapshots over time (image: Tordeux, Lämmel, et al. 2018, p. 137).

shi-2018, Fig. 2.3 (civil engineers) Shi, Lee, and Ma use a grid-based structure with square cells to model the evacuation of pedestrians in buildings. As cell size, the authors use $0.4\,\mathrm{m}$ by $0.4\,\mathrm{m}$ where multiple agents can occupy a single cell. The model uses a floor field (see Sec. 2.2.3, p. 32) to express the distance of a cell to the exit. In the floor field, diagonal directions are more costly than horizontal and vertical directions. In this floor field, the density in the target cell and the neighborhood of the current cell is used to calculate the flow into the target cell in each simulation step. The flow to a target cell is reduced if the density in a target cell is high. The flow to a target cell is high if the difference of the floor field values between the target cell and original cell is high. Shi, Lee, and Ma state that a new mesoscopic model is necessary because the computational time for microscopic models and numerous agents in large areas is insufficient. Nevertheless, they only apply their new model to a small-scale scenario to evacuate 80 agents from a square room with $6.4\,\mathrm{m}$ by $6.4\,\mathrm{m}$. In a sensitivity study, the authors calculated a density map for each simulation step, see Fig. 2.13.

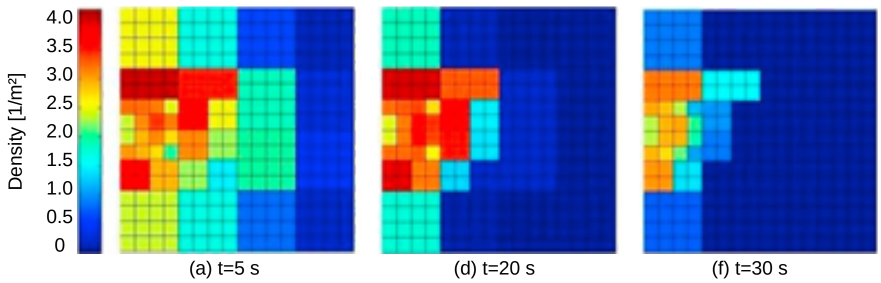


Figure 2.13: Shi, Lee, and Ma's mesoscopic model yields density maps over time for a evacuation of a square room with an exit on the left-hand side (image: Shi, Lee, and Ma 2018, p. 618, amended by own caption).

Conclusions on mesoscopic locomotion models One of the key motivations for authors to introduce mesoscopic models for pedestrian streams is to reduce the simulation time compared to microscopic approaches. While microscopic approaches model the individual characteristics of each pedestrian, mesoscopic models divide the simulation area into larger cells which can be occupied by multiple agents. Then, the flow between the cells is expressed by functions which take neighboring cells and their current density into account. All presented models except Bellomo, Piccoli, and Tosin 2012 are discrete in space. However, humans move in continuous space and their behavior is driven by this fact. Therefore, it is unsuitable to base my modeling of behavioral changes on mesoscopic models where the space is limited to cells or graphs which leads to movement artifacts (see Sec. 2.2.3, p. 29). Also authors of mesoscopic models like Bellomo, Piccoli, and Tosin explicitly use the term behavior. According to psychologist Gerrig, "behavior is the means by which organisms adjust to their environment. Behavior is action" (Gerrig 2013, p. 2). But, all mesoscopic modeling approaches presented here usually neglect the deeper processes of perception and cognition which lead to a specific behavior of humans. Only the flow between cells is modeled which depends on density and the direction to a specific target. Such a modeling approach mostly covers evacuation scenarios. This is an improvement over macroscopic modeling approaches which approximate pedestrian streams by analogies to fluids. Yet, it is not sufficient to include decision-making of individual humans properly when such models mainly move an aggregation of agents from cell to cell.

I think a better approach is to get the decisions on microscopic level "correct" from a psychological point of view. Later on, this can be embedded into a larger, mesoscopic context if computational efficiency is necessary because of large simulation areas. Many authors of mesoscopic models argue that their models are more efficient than microscopic models. For instance, Tordeux, Lämmel, et al. 2018 state that the "model is more efficient than microscopic models, and potentially more accurate than macroscopic ones." I question that efficiency is really more important than accuracy when using such simulations for improving human safety. What insights do I get from fast but "wrong" results? Nevertheless, efficient simulations are a useful tool where "real" data is hard to obtain because of ethical or logistical reasons. For example to estimate the evacuation time of a whole city as proposed in Tordeux, Lämmel, et al. 2018.

2.2.3 Microscopic locomotion models

Model definition and overview So far, I have looked at macroscopic and mesoscopic approaches to model pedestrian streams. In these approaches, pedestrians are mostly not seen as individuals. Rather their density evolution in space and time is considered. But, Wijermans concludes in her dissertation about "Understanding Crowd Behaviour: Simulating Situated Individuals" that "crowd behaviour is affected and generated by individuals" (Wijermans 2011, p. 5). Therefore, let's have a look at microscopic locomotion models which focus on individuals. According to Adrian et al. 2019, p. 8, microscopic approaches represent a "model of a particle system in which the dynamics of each particle are addressed individually (i.e. through a dedicated set of equations and/or algorithms). Examples include cellular automata and acceleration-based models."

The development of microscopic pedestrian models can be divided into three phases until now. The first phase started in 1985 when Gipps and Marksjö used the idea of a cellular automaton to describe motion of individual agents through a virtual environment (Gipps and Marksjö 1985). Gipps and Marksjö drew upon the article by physicist Wolfram in which he systematically explained cellular automata to describe dynamical and information systems in physics. In the following years, several authors used cellular automata to primarily simulate traffic flow in general and not only pedestrian streams (Nagel and Schreckenberg 1992; Rickert et al. 1996; Blue, Embrechts, and Adler 1997; Burstedde et al. 2001). The second phase of pedestrian models started in 1995, when Helbing and Molnár introduced their social force model (Helbing and Molnár 1995). Contrary to the elder cellular automaton, which is discrete in space and time, the social force model is continuous in space and time. In this model, pedestrians are driven by imaginary forces from source areas to target areas while avoiding obstacles. Helbing and Molnár were not the first authors to use forces to model pedestrian motion. Already in 1975, Hirai and Tarui used forces to simulate the "behavior of a crowd in panic" (Hirai and Tarui 1975). The third phase started at the turn of the millenium and the number of pedestrian stream models branched out. Several authors from different fields like the gaming industry, robotics and computer science introduced new models to mitigate shortcomings of existing models. Reynolds 1999 established a selection of steering behaviors to navigate autonomous characters in computer games. Berg et al. introduced a model to control "where multiple mobile robots need to avoid collisions with each other while moving in a common workspace" which is known as optimal reciprocal collision avoidance (ORCA) (Berg et al. 2011, p. 1). The computer scientists Seitz and Köster presented their new optimal space model in 2012 (Seitz and Köster 2012). The authors' goal was to introduce a locomotion which is based on simple rules like cellular automata but is not restricted to a cellular grid. They proposed to use a local discretization around agents to find the next step which allows movement in arbitrary directions and mimics the natural stepping behavior of humans. The multitude of competing models shows that there is no universally accepted locomotion model so far — and maybe there never will. There are different requirements for different applications. For instance, real-time computation of crowd motion for crowd control or step-accurate simulations to analyze clogging behavior. In the following sections, I will describe the most prominent microscopic models in more detail to assess if they can be used as basis to integrate psychological findings.

Before this, it is useful to introduce Hoogendoorn and Bovy's view for modeling pedestrian streams. In 2004, the civil engineers Hoogendoorn and Bovy proposed a new view onto microscopic modeling approaches (Hoogendoorn and Bovy 2004). They consider pedestrians as individuals and assume that pedestrians are "utility maximizers: they schedule their activities, the activity areas, and the paths between the activities" (Hoogendoorn and Bovy 2004, p. 188). Hoogendoorn and Bovy introduced a strategical, a tactical and an operational layer to guide agents through virtual environments, see Fig. 2.14, p. 31. The strategic layer represents the "motivation" of agents and controls their activity choice, that is, what an agent will do next. For instance, an agent may first buy a bus ticket at the ticket machine, then the agent goes to the bus stop. The tactical layer considers route-choice questions and how to reach the chosen activity area. This encompasses navigation and wayfinding algorithms which can include graphs and floor fields (see Sec. 2.2.3, p. 32). The operational layer carries out the actual movement to the activity area. This involves repulsion by other agents and obstacles for example.

Many existing microscopic locomotion models cover most of these layers but do not separate them so strictly.

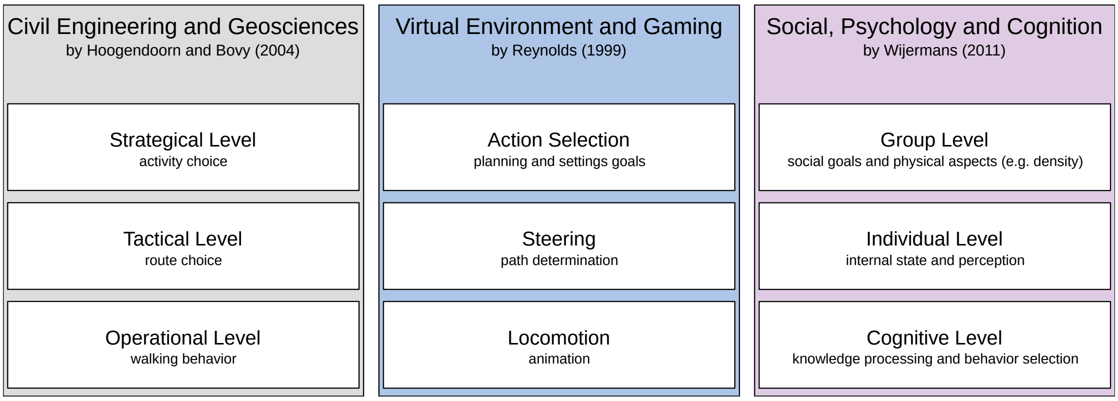


Figure 2.14: Different but similar perspectives from various authors onto microscopic approaches to model pedestrian streams.

Common ground for all microscopic locomotion models[3]

Topography All microscopic locomotion models described in the following sections share four basic modeling components: **(1)** agents — simulated pedestrians — which move from **(2)** a starting point (also called source or origin) to **(3)** a target area (also called destination) while avoiding **(4)** obstacles and other agents. These components are summarized as topography, see Fig. 2.15 (Kleinmeier, Zönnchen, et al. 2019, p. 6).

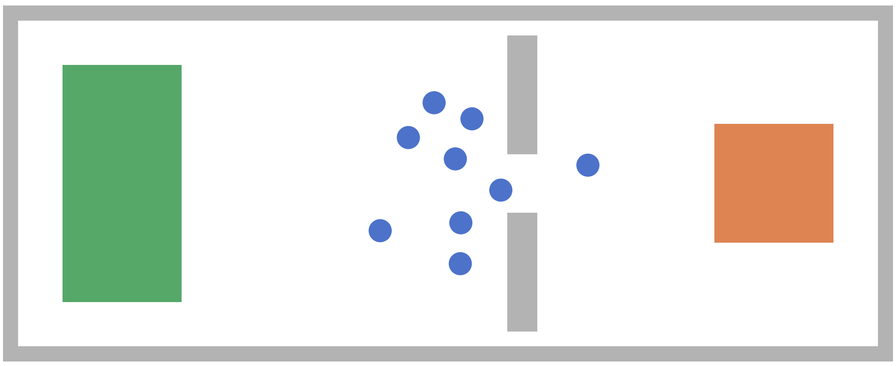
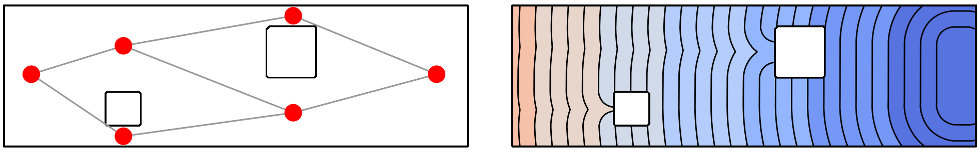


Figure 2.15: The four basic modeling components shared by different microscopic locomotion models: **(1)** agents (blue) move from **(2)** a source area (green) to **(3)** a target area (orange) while avoiding **(4)** obstacles (gray) and other agents (image: Kleinmeier, Zönnchen, et al. 2019, p. 6).

[3] The title and the first paragraph are taken from Kleinmeier, Zönnchen, et al. 2019, p. 6. The publication was a joint cooperation between Benedikt Zönnchen, Marion Gödel, Gerta Köster and me. The title and the first paragraph reflects my own thoughts which apply to all microscopic locomotion models and are also helpful for readers of this dissertation.

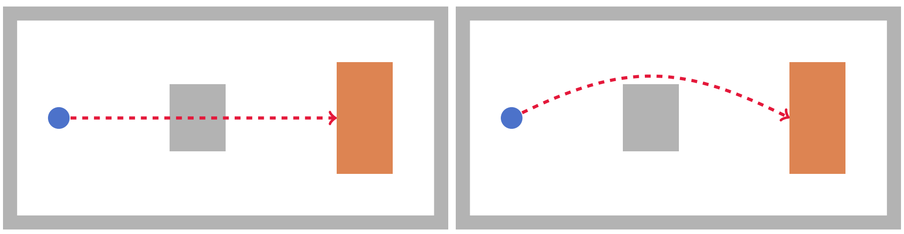
Agent navigation by graphs or floor fields One central aspect of microscopic locomotion models is how agents find the direction to their target. One can distinguish two approaches: graph-based navigation and floor-based navigation, see Fig. 2.16.



(a) A graph-based navigation approach. **(b)** A floor-field-based navigation approach (image: Kleinmeier, Zönnchen, et al. 2019, p. 7).

Figure 2.16: Navigation of agents by graphs or floor fields in a topography with two obstacles (white). The source area is on the left-hand side and the target area is on the right-hand side.

Graph-based navigation uses so called orientation points (Hartmann 2010) which are distributed within the topography, either heuristically or randomly. Agents can then walk from orientation point to orientation point by using graph algorithms, see Fig. 2.16 (a). Common graph algorithms are the Dijkstra algorithm and the corridor map method (Dijkstra 1959; Geraerts and Overmars 2007). The common idea behind floor fields is that they encode the distance to the target for every point of the topography. That is, the topography must be discretized and for each grid point the distance to a target is calculated. A simple approach is to calculate the Euclidean distance to the target which leads to drawbacks when obstacles are between the considered point and the target. More elaborated approaches calculate the geodetic distance to the target which takes impermeable obstacles into account. Fig. 2.17 visualizes the difference between the Euclidean and geodetic distance.



(a) The Euclidean distance. **(b)** The geodetic distance.

Figure 2.17: Two options for navigating agents trough the topography by using either the Euclidean or the geodetic distance to a target (image: Kleinmeier, Zönnchen, et al. 2019, p. 6).

The geodetic distance can be mathematically expressed by the eikonal equation Eq. 2.19. The eikonal equation physically describes the propagation of a wave front, see Fig. 2.18.

$$|\nabla u(x)| = \frac{1}{f(x)}, \quad x \in \Omega \tag{2.19}$$

where Ω represents the topography in $\mathbb{R}^n$, $f(x)$ is a function with positive values, ∇ denotes the gradient and $|\cdot|$ the Euclidean norm. The solution $u(x)$ for the eikonal equation is the shortest travel time from x to a specified target inside Ω. $f(x)$ is provided as input to the eikonal equation and characterizes the material properties at point x.

Using large values for $f(x)$ speeds up the wave propagation and yields a small gradient $|\nabla u(x)|$. A small gradient (in $\mathrm{s/m}$) means that a short time is needed to travel a certain distance. Sethian's fast marching method is a computational algorithm to solve the eikonal equation numerically.

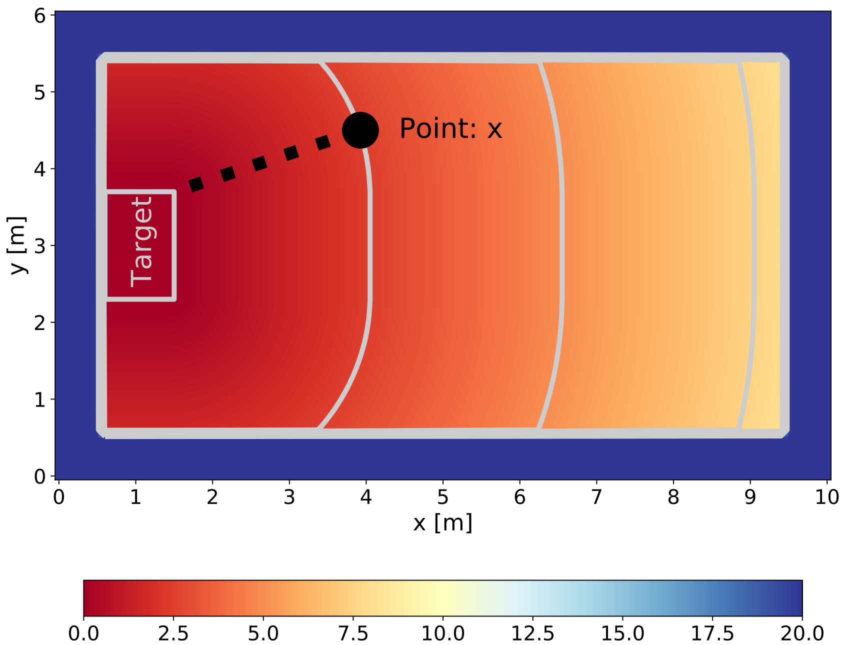


Figure 2.18: The figure shows the expansion of a propagating wave front in a corridor with $10\,\mathrm{m} \times 6\,\mathrm{m}$ (length $\times$ width). The corridor is enclosed with a wall of $0.5\,\mathrm{m}$ which cannot be penetrated by the wave (the speed $f(x)$ of the wave inside the wall is zero). Outside the wall, a constant speed of $1\,\mathrm{m/s}$ is assumed. The initial wave front is given by the curvature around the target. The decreasing color intensity from a darker red to a lighter red visualizes the increasing distance to the target curvature. Blue color tones show an even greater distance to the target. The gray contour lines indicate the propagating wave front.

Burstedde et al. 2001 introduced floor fields when they investigated pedestrian streams using a cellular automaton. Later, this idea was reused for other microscopic pedestrian locomotion models like the optimal steps model (Hartmann 2010; Zönnchen 2013). Graph-based approaches allow fast navigation in large scenarios compared to floor fields but can yield unrealistic trajectories.

Model examples

Cellular automata (gipps-1985, Fig. 2.3) While John von Neumann introduced the general concept of cellular automata in 1966, the physicist Wolfram 1984 refined it to analyze dynamical and information systems in 1984 (Wolfram 1984). According to Wolfram's definition, a cellular automaton consists of cells which the author denoted as a_i: "The value a_i of the site at each position i is updated in discrete time steps according to an identical deterministic rule depending on a neighborhood of sites around it" (Wolfram 1984, p. 419). Gipps and Marksjö 1985 were the first authors who applied this concept to model pedestrian streams. That is, agents are moved from cell to cell towards a target by taking the neighboring cells into account. Fig. 2.19 visualizes the concept of a cellular automaton for pedestrian dynamics.

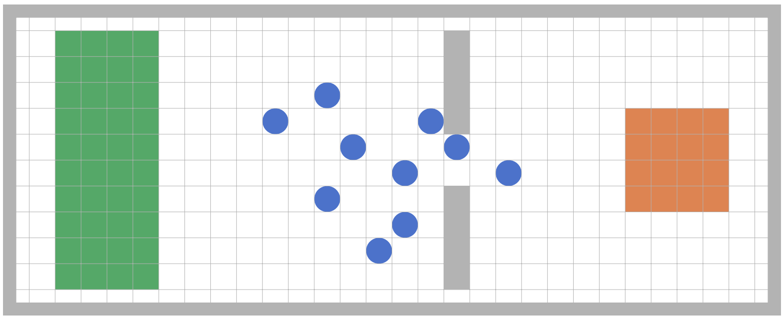


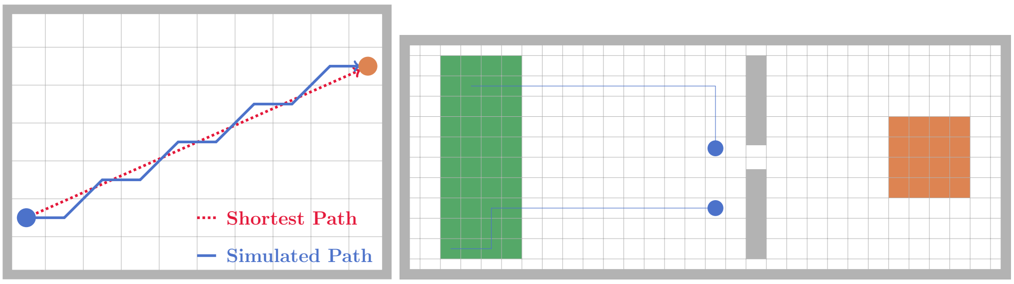
Figure 2.19: The concept of a cellular automaton with the common grid structure (image: Kleinmeier, Zönnchen, et al. 2019, p. 9).

The pedestrian dynamics community adopted the simple idea of cellular automata and developed several extensions. In 1997, Blue, Embrechts, and Adler added special evasion rules for agents to let agents evade only if the space towards the target is occupied (Blue, Embrechts, and Adler 1997). Fukui and Ishibashi used a cellular automaton to simulate car traffic in 1999 (Fukui and Ishibashi 1999). A significant improvement was introduced in 2001, when Burstedde et al. applied the concept of floor fields to cellular automata to achieve long-range interactions of agents (Burstedde et al. 2001). A floor field allows agents to better estimate the distance to the target by taking obstacles into account and to evade them at an early stage. In 2003, Klüpfel used floor fields and added a preferred movement direction to each cell (Klüpfel 2003). In 2006, Wąs, Gudowski, and Matuszyk introduced a cellular automaton taking the social space concept into account which was originally proposed by the anthropologist Hall in 1966 (Wąs, Gudowski, and Matuszyk 2006). By observing animals and American men, Hall identified four well-respected spaces (distances) around humans and animals: the intimate space ($0\,\mathrm{m}$ to $0.5\,\mathrm{m}$; from center of body), personal space ($0.5\,\mathrm{m}$ to $1.2\,\mathrm{m}$), social space ($1.2\,\mathrm{m}$ to $3.0\,\mathrm{m}$) and public space ($3.0\,\mathrm{m}$ and above), see Hall 1966, p. 113–131. Different authors, e. g. Leng et al. 2014, use hexagon cells instead of square cells. Newer approaches like Feliciani and Nishinari 2016a try to mitigate shortcomings of the regular grid structure by introducing sub-meshes to allow higher densities than regular cellular automata.

Cellular automata are easy to understand and fast to compute even for larger simulation areas. However, the fixed spatial discretization limits the step length and the physical size of agents artificially. Additionally, the spatial discretization causes movement artifacts, see Fig. 2.20.

Social force model (helbing-1995, Fig. 2.3) The physicists Helbing and Molnár introduced their social force model in 1995 as an alternative draft to the existing cellular automata to study pedestrian motion (Helbing and Molnár 1995). In the social force model, the movement of a pedestrian α is determined by four factors where arrows denote vector quantities:

1. The difference between the current velocity $\vec{v}_\alpha$ of a pedestrian α and its preferred velocity $\vec{v}_\alpha^0$.



(a) A zig-zag trajectory because of the regular grid structure.

(b) A too coarse grid hinders agents to pass a narrow passage.

Figure 2.20: Movement artifacts produced by cellular automata (image: Kleinmeier, Zönnchen, et al. 2019).

2. The direction $\vec{e}_\alpha$ to the target.
3. The repulsion by another pedestrian β and wall B (depending on their position r).
4. The attraction to other objects i.

The total force $\vec{F}_\alpha$ acting upon a pedestrian α at time t is then defined by Eq. 2.20.

$$\begin{aligned}\vec{F}_\alpha = & \underbrace{\vec{F}^0_\alpha(\vec{v}_\alpha, v^0_\alpha \vec{e}_\alpha) + \sum_\beta \vec{F}_{\alpha\beta}(\vec{e}_\alpha, \vec{r}_\alpha - \vec{r}_\beta)}_{\text{preferred velocity to target and pedestrian repulsion}} \\ & + \underbrace{\sum_B \vec{F}_{\alpha B}(\vec{e}_\alpha, \vec{r}_\alpha - \vec{r}^{\alpha}_B)}_{\text{wall repulsion}} \\ & + \underbrace{\sum_i \vec{F}_{\alpha i}(\vec{e}_\alpha, \vec{r}_\alpha - \vec{r}_i, t)}_{\text{object attraction}} \end{aligned} \tag{2.20}$$

Helbing and Molnár combined these factors as second-order differential equation of motion to take acceleration of pedestrians into account. The change in the position dw_α is described as

$$\frac{dw_\alpha}{dt} = \vec{F}_\alpha + \text{randomness} \tag{2.21}$$

The social force model can be solved by numerical methods for ordinary differential equations like Runge-Kutta. The model is able to yield natural-looking trajectories because it is continuous in space and time opposed to the zig-zag trajectories which can be observed by cellular automata. Lane formation is one well-known emergent effect of the model, see Fig. 2.21, p. 36. However, the various forces in the model can lead to oscillating trajectories. Like all differential-equation-based models it can suffer from mathematical instabilities and numerical pitfalls like described in Köster, Treml, and Gödel 2013.

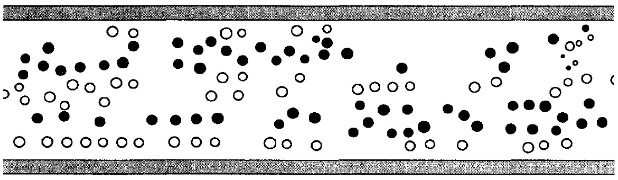


Figure 2.21: Lane formation is one well-known emergent effect of the social force model. Helbing and Molnár simulated a $50\,\mathrm{m} \times 10\,\mathrm{m}$ (length $\times$ width) walkway with agents walking in different directions represented by empty and full circles (image: Helbing and Molnár 1995, p. 51).

Reynolds's steering behaviors for autonomous characters (reynolds-1999, Fig. 2.3) Reynolds presented his steering behaviors after working for several gaming and animation companies for twelve years (Reynolds 1999, p. 18). The proposed behaviors originate in the gaming industry to control autonomous characters through virtual environments. The basis of the steering behaviors is the motion equation from physics. The equation states that a new position x_{new} of a point mass can be obtained by using the old position x_{old}, the current velocity v and the acceleration a of the point mass: $x_{\text{new}} = x_{\text{old}} + vt + \frac{1}{2}at^2$, where t is a given time interval. Reynolds uses the pseudo code in List. 2.1, p. 37, to express the motion equation. He proposes different behaviors which only modify the acceleration term `steering_force` in List. 2.1. For instance, the seek behavior uses the vector between a target and the current position to modify the term `steering_force` while the flee behavior uses the opposite direction of this vector, see Fig. 2.22. The pursuit behavior permanently calculates a vector between a moving target and the current position to continuously adapt the acceleration term. In total, Reynolds proposes 18 behaviors in Reynolds 1999: seek, flee, pursuit, evasion, offset pursuit, arrival, obstacle avoidance, wander, path following, wall following, containment, flow field following, unaligned collision avoidance, separation, cohesion, alignment, flocking, and leader following. The proposed behaviors can be combined, either sequentially or they can be blended together by simply summing multiple acceleration vectors. Reynolds proposes a wide range of behaviors but does not provide empirical evidences for his modeling approaches.

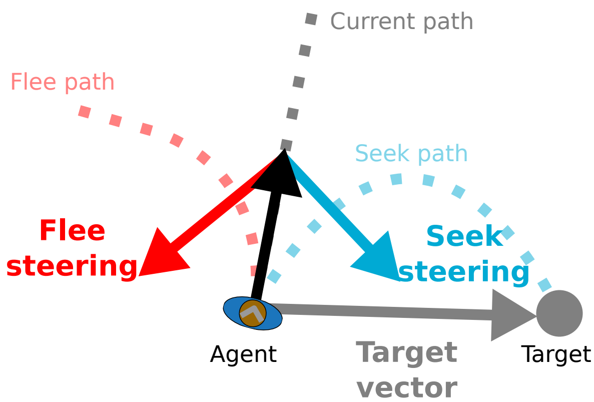


Figure 2.22: In Reynolds's model the "Target vector" is used to derive different steering strategies, for instance, seek or flee which results in different agent paths.

Listing 2.1: The position calculation of agents proposed by Reynolds 1999, p. 7.

```
// Note: "max_force" and "max_speed" are constants
steering_force = truncate(steering_direction, max_force)
acceleration   = steering_force / mass
velocity       = truncate (velocity + acceleration, max_speed)
position       = position + velocity
```

Optimal reciprocal collision avoidance (berg-2011, Fig. 2.3) In 2011, the computer scientists Berg et al. presented a new model which addresses the problem of multiple moving robots that need to avoid collisions with each other while moving in a shared workplace (Berg et al. 2011). The model is abbreviated as ORCA (optimal reciprocal collision avoidance) and ensures that robots can move collision-free at least for a fixed amount of time τ into the future. Optimal refers to the fact that each robot A tries to reach its preferred velocity v_A^{pref}. Reciprocal means that each robot A chooses a new speed v_A^{new} independently and simultaneously just by observing the local neighborhood.

To this end, the authors firstly define how two robots A and B can move in a collision-free way. Then, they extend this idea to move n robots in a collision-free way. To move two robots A and B without collisions, they define a mathematical set called "velocity obstacle" $VO_{A|B}^{\tau}$ which contains all velocities that lead to collisions between robot A and B. Geometrically, this set represents a truncated cone with its apex at the origin of the velocity space (with origin $v_x = 0$ and $v_y = 0$, see Fig. 2.23 (b)). Additionally, the authors define a second set of "collision-avoiding" velocities $CA_{A|B}^{\tau}$. This set for robot A represents the complement of the Minkowski sum of $VO_{A|B}^{\tau}$ and V_B, where V_B contains the velocity which is chosen by robot B (and observed by robot A). Fig. 2.23 visualizes this concept.

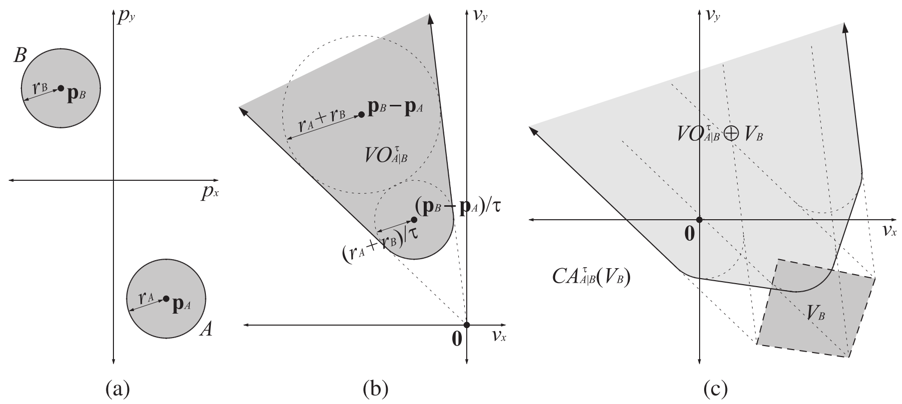


Figure 2.23: Collision avoidance in the ORCA model: **(a)** The position of robot A and B in the Cartesian space. **(b)** The set "velocity obstacle" $VO_{A|B}^{\tau}$ which contains all velocities that lead to collisions between robot A and B in the velocity space. **(c)** The set of "collision-avoiding" velocities $CA_{A|B}^{\tau}$ which represents the complement of the Minkowski sum of $VO_{A|B}^{\tau}$ and V_B (image: Berg et al. 2011, p. 5).

The authors demonstrated the efficiency of the model by simulating an evacuation of an office building with 1000 agents, see Fig. 2.24, p. 38. But, the authors did not validate their results against empirical data.

Figure 2.24: Berg et al. used their ORCA model to simulate an evacuation of an office building with 1000 agents (image: Berg et al. 2011, p. 5).

Optimal steps model (seitz-2012, Fig. 2.3) The computer scientists and mathematicians Seitz and Köster proposed their optimal steps model in 2012 (Seitz and Köster 2012). Their goal was to describe pedestrian movement with simple rules, like cellular automata, but do not restrict this movement to a cellular grid. They were inspired by the stepwise movement of humans and consequently they use a local discretization around agents which allows movement in arbitrary direction and different step lengths. The direction of an agent is influenced by three factors:

1. The attraction towards a target t.
2. The repulsion by other agents.
3. The repulsion by obstacles.

The target attraction is represented as floor field (see Sec. 2.2.3, p. 32). The repulsion to other agents and obstacles depends on the Euclidean distance to them and is expressed by potential functions that try to replicate the graph of a Gaussian bell curve around the agent or the obstacle. That is, the repulsion is high when being close to the agent's or the obstacle's center and it decreases when further away from its center. The target potential at point x in the plane is denoted as $P_t(x)$, the agent potentials as $P_p(x)$ and the obstacle potentials as $P_o(x)$. For each pedestrian l the authors form an aggregated potential, Eq. 2.22.

$$P_l(x) = P_t(x) + \sum_{i=1, i \neq l}^{n} P_{p,j}(x) + \sum_{j=1,}^{m} P_{o,j}(x), \tag{2.22}$$

with n pedestrians and m obstacles in the scenario. The next position of an agent is the minimum of all potentials. The minimum is searched within a certain radius around the agent which depends on the current speed of the agent, see Fig. 2.25. The authors argue that these potentials should be interpreted as utility to address the idea of a "homo oeconomicus" who maximizes its utility instead of searching a minimum potential. However, the mathematical description is equivalent: the potentials change the sign and agents search the maximum utility instead of the minimum potential. The model was extended by a personal space concept (Sivers and Köster 2014) which makes agents to keep a certain distance from each other to mimic the human's need for a personal space (Hall 1966).

The optimal steps model reproduces well-known fundamental diagrams by Weidmann 1993 and allows different step lengths like humans do in real world which is validated against empirical data (Sivers, Köster, and Kleinmeier 2016), see Fig. 2.26. The model is

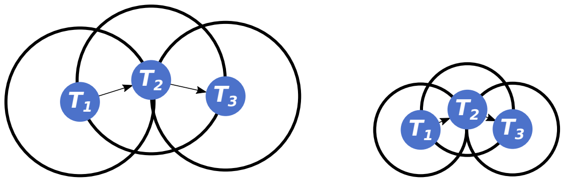


Figure 2.25: In the optimal steps model, agents search their next step in a radius which depends on the current speed. The figure shows three consecutive time steps of a fast agent (left) and a slow agent (right).

computational expensive when simulating thousands of agents because a mathematical optimization problem must be solved in each simulation step.

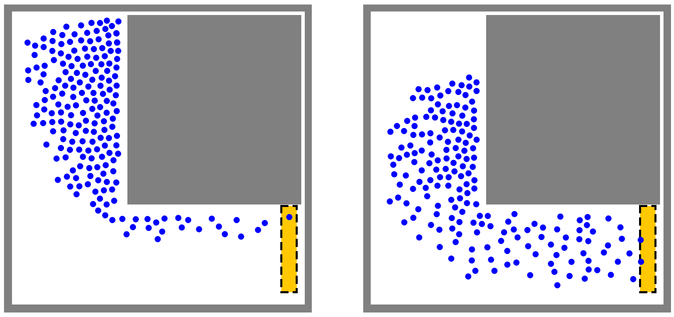


Figure 2.26: Seitz and Köster tested their optimal steps model against several small-scale real-world scenarios. The simulation shows how 200 agents walk around a corner with different parameter sets of the optimal steps model (image: Seitz 2016, p. 69).

Gradient navigation model (dietrich-2014, Fig. 2.3) The mathematicians Dietrich and Köster introduced a new microscopic locomotion model in 2014 (Dietrich and Köster 2014). It is based on a set of ordinary differential equations to determine the position $x \in \mathbb{R}^2$ of each pedestrian i at any point in time. The proposed model uses a velocity field instead of a force field like the social force model. Therefore, it does not include an acceleration aspect but changes the velocity vector directly. An agent's direction is instantly adapted without acceleration over time.

Similar to the optimal steps model it combines a target attraction and repulsion by agents and obstacles. All factors are expressed by gradients. The target attraction $\vec{N}_{i,T}$ for target T and pedestrian i which is heading to target T is derived from the underlying floor field ϕ which is based on the eikonal equation, see Eq. 2.23. The repulsion is also achieved by gradients to neighboring agents j and obstacles B, see Eq. 2.24.

$$\underbrace{\vec{N}_{i,T} = -\nabla\phi,}_{\text{target attraction}} \tag{2.23}$$

where ϕ denotes the solution of the eikonal equation.

$$\vec{N}_{i,P} = -\left(\underbrace{\sum_{j \neq i} \nabla P_{i,j}}_{\text{pedestrian repulsion}} + \underbrace{\sum_{B} \nabla P_{i,B}}_{\text{obstacle repulsion}} \right), \tag{2.24}$$

where $\nabla P_{i,j}$ and $\nabla P_{i,B}$ are gradients of functions that are based on the distance of pedestrian i to another pedestrian j and obstacle B respectively. The gradient for the target attraction $\vec{N}_{i,T}$ and the gradient for repulsive factors $\vec{N}_{i,P}$ influence the next position x of a pedestrian.

The authors successfully validated their gradient navigation model against empirical data. The model reenacted the flow rate according to Liddle et al. 2011 and the speed-density relation according to Weidmann 1993 in an unidirectional bottleneck scenario. Also, the authors observed stop-and-go waves when a certain global density is reached.

Behavioral heuristics model (seitz-2016c, Fig. 2.3) Based on their experiences with the optimal steps model, Seitz, Bode, and Köster proposed an additional model in 2016 which describes pedestrian movement with only four heuristic rules which also represent their cognitive effort (Seitz, Bode, and Köster 2016). As in other models, agents are attracted by a target. To reach this target, agents use four heuristic rules: **(1)** If the space in front of an agent is clear, the agent steps to it. Otherwise, the agent waits. **(2)** A second heuristic allows agents to evade tangentially, if the space in front is occupied but space next to it is free. **(3)** As third option, an agent can evade sideways if the whole area in front of the agent is blocked. **(4)** A last heuristic allows agents to follow other agents. Each heuristic is cognitively more demanding than the previous one because it requires more collision checks. Fig. 2.27 summarizes the four movement heuristics introduced by Seitz, Bode, and Köster.

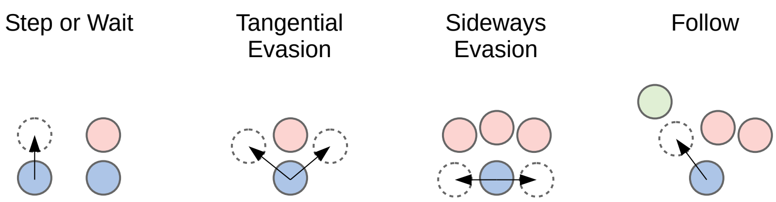


Figure 2.27: Seitz, Bode, and Köster propose four heuristics to navigate agents towards a target (image: Kleinmeier, Zönnchen, et al. 2019, p. 13).

The authors tested their behavioral heuristics model with a bottleneck scenario which is based on a real experiment. Seitz, Bode, and Köster revealed that enabling and disabling different heuristics lead to different shapes for the waiting agents in front of the bottleneck. The behavioral heuristics model is an intuitive idea to move agents through virtual environments even if it is not fully developed yet. For instance, a fixed step length is used which does not reflect movement of humans. Until now, it was only applied to very simple geometries and not larger real-world scenarios.

Model extensions The last sections showed that there is a wide range of microscopic pedestrian models and even a wider range of model extensions exists. For instance, Yanagisawa; Xue et al. extended cellular automata to overcome deadlock situations in bidirectional pedestrian flows based on a more cooperative behavior of agents (Yanagisawa 2016; Xue et al. 2020). Feliciani and Nishinari extended a cellular automaton to allow greater densities and enabled swapping strategies for agents to maintain flow in counterflow scenarios (Feliciani and Nishinari 2016a). Other modelers let agents evade tangentially or sideways in force-based models (Feliciani and Nishinari 2016a). Sivers, Templeton, et al. extended the optimal steps model to include helping behavior of agents (Sivers, Templeton, et al. 2016). All these aspects show that there is no universally accepted locomotion model and many modeling approaches are not reusable.

Conclusions on microscopic locomotion models Microscopic models try to capture the stepping behavior of each agent individually instead of interpreting all agents as a continuum like macroscopic models do and partially mesoscopic models do. Therefore, microsopic models suit best to include psychological aspects because these aspects affect each agent individually and not the whole agent continuum. The overview of microscopic models also revealed that there is no universally accepted microscopic locomotion model at the moment, see Fig. 2.28, p. 42, — and maybe there never will be one, because each model has strengths and also weaknesses.

For instance, the widely used cellular automata (see Fig. 2.28) are computational fast but are discrete in space which limits the agent movement to fixed cells. The social force model is continuous in space but is based on differential equations and does not allow real interaction between agents except pushing and pulling forces which makes it hard to include psychological aspects. The optimal steps model is not based on differential equations. It rather solves an optimization problem for each agent individually in each simulation step to find the next step of an agent. Agents can better interact with each other which makes it a preferable choice to include my findings even if it is computational expensive for a large number of agents. The other models are not sufficiently validated against empirical data at the moment.

Introduced	**Model name**	**Search term** pedestrian	crowd
1985	cellular automaton	6150	6040
1995	social force model	7690	6870
1999	reynolds steering	277	351
2011	optimal reciprocal collision avoidance	313	311
2012	optimal steps model	87	73
2014	gradient navigation model	63	61
2016	behavioral heuristics model	6	6

Table 2.2: Search results for different microscopic locomotion models on `https://scholar.google.com/` to “measure” the popularity and acceptance. For each model, two search queries were carried out on Nov 12, 2020. First, the model name was combined with the term “pedestrian”. Then, the model was combined with the term “crowd”. The name of the model was enclosed in quotation marks to search the exact pattern.

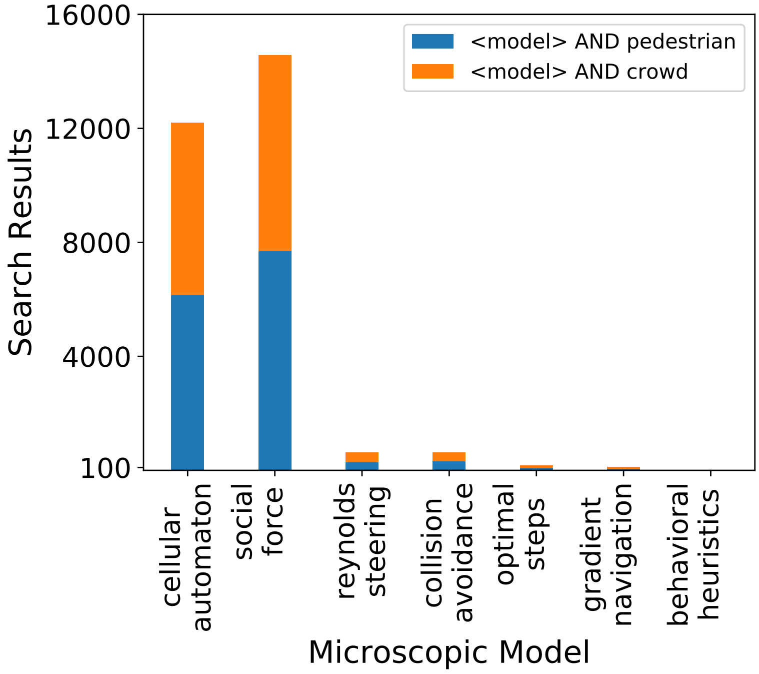


Figure 2.28: The popularity of different microscopic locomotion models by counting search results on `https://scholar.google.com/` on Nov 12, 2020.

2.3 Pedestrian stream models including psychology

Currently, most of the presented modeling approaches only take physics into account to replicate pedestrian streams, but neglect psychological and sociological effects when humans come together. For this reason, I would like to shed light onto which models exist that include some sort of psychology and what aspects are helpful to answer the research question: how can changes in human behavior be operationalized for simulations?

One can distinguish two categories when looking at models including psychological aspects: explanatory and predictive models. The latter model type focuses on moving simulated agents through virtual environments, for instance, to detect critical high densities. The former model also uses “agents”, but here, an agent is a wrapper to store human-like psychological attributes like a stress level. In contrast to predictive models, explanatory models usually do not move agents through virtual environments. Instead, explanatory models are used to carry out numerical simulations to find causing effects, for example, if the stress level influences an agent’s memory.

2.3.1 Explanatory models

Different research communities contribute and describe models which include psychological aspects for agent-based simulation approaches. Surprisingly, mainly the multi-agent community proposes a wide range of models. In 2014, Balke and Gilbert conducted a survey to distill 14 models which are suitable for integration in agent-based simulations (Balke and Gilbert 2014). It is worth to introduce approaches from this community with an important note in advance: on the one hand, researchers from a multi-agent background usually do not have a well-educated psychological background. But, they are experts in the actual implementation of models. On the other hand, researchers from life sciences like psychology and sociology provide long, verbal descriptions for modeling but usually lack any implementation. Thus, the usefulness of a model cannot be fully assessed.

Most of these publications presented in the following originated in the multi-agent community where the term "agent" is described as following: "We consider agents to be systems that are situated in some environment. By this, we mean that agents are capable of sensing their environment (via sensors), and have a repertoire of possible actions that they can perform (via effectors or actuators) in order to modify their environment" (Bordini, Hübner, and Wooldridge 2007, p. 2). Contrarily to the pedestrian dynamics community, the focus lies more on cognitive information processing to coordinate the knowledge and goals of multiple agents rather than steering agents through virtual environments. Therefore, the multi-agent community mostly proposes computational logic and logic languages like Prolog to describe behavior in agent-based systems (Balke and Gilbert 2014, p. 5). This makes them not very attractive for current pedestrian stream simulators which are usually based on object-oriented languages like C++ or Java.

In the following, I will shortly summarize the approaches proposed in Balke and Gilbert 2014 to model decision-making of virtual agents. I categorize and summarize the modeling approaches in table Tab. 2.3. When applying Hoogendoorn and Bovy's three-layer architecture from Fig. 2.14, we see that all of these approaches only cover the topmost layer, the strategic level. The approaches completely neglect the actual movement of agents.

- **Production rules:** In production rule systems, the behavior of agents is based on the inputs an agent perceives and is expressed by simple if-then-else statements. Formally, a production rule system consists of three components (Balke and Gilbert 2014, p. 4):

  1. A set of rules (called productions in literature) in the form $C_i \rightarrow A_i$: upon condition C_i the action A_i follows.
  2. One or more knowledge databases which describe the state of the environment of an agent.
  3. A rule interpreter which determines the order of the rules when applying the rules against the knowledge database.

  Usually, each agent-based modeling and simulation approach uses simple if-then-else chains to steer agents through virtual environments even if not explicitly implementing the three formal components of a production rule system. That is, first agent-based systems test an agent's environment — the if-part of production rules — and then the actual steering part follows. Production rules are not a completely new approach to model agent behavior but a more formal approach which was initially proposed by Nilsson 1977.

- **Intentional models:** The idea of intentional models for human decision-making arrived roughly a decade after the production rule systems. They are based on philosophers Bratman's view that three components determine human's behavior:

Model category	**Model examples**	**Characteristic**
Production rules	-	Agents follow simple if-then-else rules.
Intentional model	• BDI: Beliefs Desires Intentions • eBDI: Extended BDI • BOID: Beliefs Desires Obligations Intentions • BRIDGE	Agents follow believes, desires and intentions.
Normative model	• Deliberative Normative Agents • EMIL-A: EMergence In the Loop Agent Architecture • NoA: Normative Agents	Agents obey social and legal norms.
Cognitive model	• PECS: Physical conditions, Emotional state, Cognitive capabilities and Social status, • Consumat	Agents take more aspects into account than intentional models, e. g. an emotional state or a stress level.
Neurological model	• ACT-R/PM: Adaptive Control of Thought-Rational/ Perceptual-Motor • CLARION (neural network) • SOAR: Symbolic (cognitive) Architecture	Agents use a short- and long-term memory to derive behavior.

Table 2.3: Theoretical models from multi-agent community for agent-based simulations.

beliefs, desires and intentions. In agent-based simulations, beliefs represent the information that an agent has about the world. Desires are tasks an agent might like to accomplish. For instance, leave the building. Sometimes, desires are also referred to as goals. Finally, the intentions represent a specific course of action to fulfill a desire. The beliefs, desires and intentions are updated in each simulation step. Many extensions were developed for the original BDI model which is described in detail in the book Bordini, Hübner, and Wooldridge 2007. The eBDI model (emotional beliefs desires intention) proposes to add emotions as part of an agent's decision-making process (Pereira, Oliveira, and Moreira 2008). The BRIDGE model proposes that not only beliefs, desires and intentions influence an agent's behavior (Dignum and Dignum 2009). There are three other factors that should be taken into account: the ego, responses and goals. The ego represents personal preferences. For instance, some commuters prefer the subway to the car. Additionally, responses to environmental stimuli influence the selection of goals. In summary, the factors beliefs, responses, intentions, desires, goals and ego are the core components of the BRIDGE model. The BOID model (beliefs obligations intentions desires) extends the classic BDI model by obligations of an agent and is step towards normative models (Broersen et al. 2001). Obligations or “social rules” influence the behavior of an agent.

- **Normative models:** The central aspects to control agents in normative models are norms and social rules. While intentional models focus on the internal motivation of humans, normative models highlight the importance of external motivation. This external motivation is affected by laws and social norms. For instance, it is forbidden to drive over a red traffic light. It is suggested that such social norms are recognized by agents through observing the environment or via communication with other agents (Balke and Gilbert 2014, p. 13). As in BDI models, it is suggested that agents perceive their environment (as part of the beliefs component in BDI models). But now, the selection of desires is influenced by norms. Kollingbaum and Norman argue that norms are not only filters for the selection of desires (Kollingbaum and Norman 2004). Norms involve more considerations. Therefore, it is an own model category. Model examples are: the deliberate normative agents (Conte, Castelfranchi, and Dignum 1999), the normative agent (NoA) of Kollingbaum and Norman 2004 and the EMIL architecture presented in Andrighetto et al. 2007.

- **Cognitive models:** The goal of cognitive models is to improve social simulations so that simulated agents do not only carry out one single custom-tailored task, for instance, to reach the next exit as quickly as possible. Agents should be able to carry out more tasks by perceiving their environment, processing this information by taking emotions, cognitive capabilities and the social status into account and derive an appropriate behavior. The PECS model (physics, emotions, cognition, social status) is a prominent cognitive model (Urban 2000).

- **Neurological models:** Neurological models are heavily related to cognitive models. The main difference is that they include a sort of memory in the cognitive process. Agents store past experiences in a short- or long-term memory. This memory influences future decisions and shall convert agents to learning creatures. In contrast to the previously mentioned cognitive models, the cognitive process is more granular. Model examples are CLARION (Connectionist Learning with Adaptive Rule Induction ON-line) in Sun and Peterson 1996, ACT-R (Adaptive Control of Thought-Rational) and its extension ACT-R/PM in Taatgen, Lebiere, and Anderson 2005 and the symbolic cognitive architecture SOAR in Laird, Newell, and Rosenbloom 1987.

My fundamental critique on these models Except production rules, all of the presented models try to mimic human cognitive and decision-making processes as closely as possible. For instance, Balke and Gilbert 2014, p. 12 state that “autonomous entities such as agents need to be able to reason, communicate and negotiate about norms, including deciding whether to violate social norms [...]”. But, how does such a negotiation look like? Through eye contact? Or a (long-running) milling process between participants like proposed by social psychologists (Turner and Killian 1957)? The authors do not provide any details about the essential modeling aspects.

In my opinion, a model which is suitable for simulations should be understandable and not too complex. That is, a simplification of the reality. Otherwise, the actual implementation gets error-prone and simulation results cannot be validated because a model requires too much parameters. These explanatory models are too theoretic and too complex, compare Fig. 2.29. There is a large gap between these models and an actual implementation in real pedestrian simulators. But, these model approaches give an idea what is important when considering decision-making of humans and simulated agents. For example, most models propose to include perception as a central component.

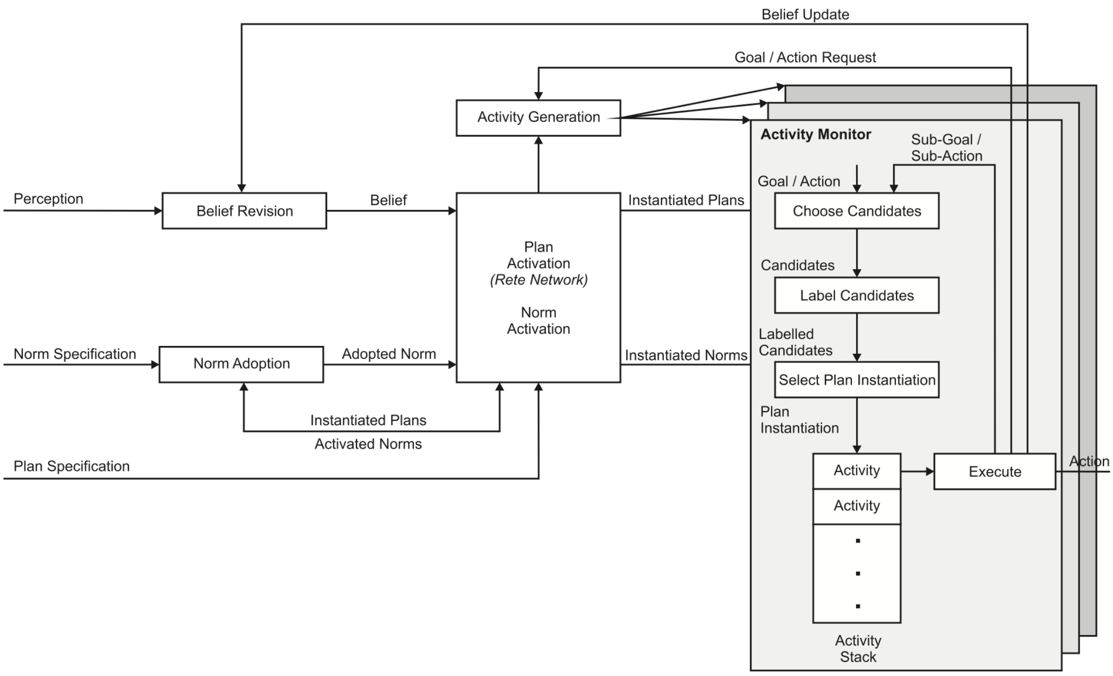


Figure 2.29: The complexity of existing explanatory models for agent-based simulations exemplified by the Normative Agent (NoA) model (image: Balke and Gilbert 2014, p. 16).

2.3.2 Predictive models

Some authors already tried to integrate psychological aspects into current pedestrian stream simulators and validated their results. The following section provides a chronological overview of these approaches. In contrast to the previous section, they focus on steering agents through virtual environments instead of coordinating multiple agents.

- **Pelechano, O'Brien, et al. 2005:** The authors combine an existing locomotion framework called MACES with the existing framework PMFserv that implements human behavior models. MACES stands for "Multi-Agent Communication for Evacuation Simulation" and computes the agent navigation on two levels. The high level yields a sequence of rooms to the exit and the low level uses the social force model to steer the agents. The MACE framework allows agents to share information about the environment, e. g. hazards or closed doors. PMFServ stands for "Performance Moderator Functions" and is a software library that covers a decision-making process based on the emotional state of an agent which is influenced by stress and physiological factors. In their publication, the authors focus on evacuation scenarios.

- **Pan 2006:** The dissertation of the civil engineer Pan deals with the "computational modeling of human and social behaviors for emergency egress analysis". Pan's goal is to integrate diverse human behaviors in the existing simulator MASSEgress (Multi-Agent Simulation System for Egress analysis). In the dissertation, Pan equips agents in MASSEgress with sensors to perceive environmental cues, a "brain" to process this information and adapt the behavior accordingly. Following behaviors are available for egress situations: explore, go to goal point, compete at exit, queue at exit, follow a leader and follow an agent.

- **Pelechano, Allbeck, and Badler 2007:** The authors extended their previous model from 2005 (Pelechano, O'Brien, et al. 2005). They replace the external library PMFserv by their own implementation. Their own implementation covers perception and a set of reactive behaviors: queuing, pushing behavior, falling and becoming obstacles, panic propagation and avoiding bottlenecks. The authors rename their simulator from MACES to HiDAC (High-Density Autonomous Crowds) which shifts the focus away from only evacuations.

- **Wijermans 2011:** Wijermans focuses on the question of understanding crowd behaviors. She develops and implements a model to simulate festivalgoers in her dissertation. The model is called CROSS which stands for crowd behaviour that simulates situated individuals. In the model, Wijermans introduces multiple physiological parameters like arousal and bladder which affect an agent's behavior. The CROSS model was promoted in a dedicated paper two years after the dissertation (Wijermans et al. 2013).

- **Bosse et al. 2013:** This represents an exhaustive extended Beliefs Desire Intention (eBDI) implementation. The authors focus more on how agents share and change their beliefs/desire/intention status than on obtaining accurate pedestrian streams. The model is used to analyze a false alarm during a WWII ceremony at the Dam Square in Amsterdam 2010 and how the visitors came to a collective decision to flee. The authors describe the scenario as following: "The panic spread through the people that were running away who infected each other with their emotions and intentions to flee" (Bosse et al. 2013, p. 64–65).

- **Sivers 2016:** Sivers integrates three concepts from social psychology into the open source simulator Vadere (see Sec. 5.2, p. 80). In her dissertation, she focuses on the personal space of pedestrians, the social identity theory and search strategies. The dissertation was a first proof of concept that theories from social psychology can be systematically integrated into existing pedestrian stream simulators.

- **Kielar 2017:** In his dissertation, Kielar develops a model for a sequential destination selection. The model is called SPICE, for spatial destination choice. Kielar draws upon the three-layer architecture of Hoogendoorn and Bovy 2004 with a strategic, tactical and operational layer. The author extends this architecture by several modules to allow a sequential destination selection. These modules comprise perception, a memory and individual preferences of agents and are implemented in the open-source MomenTUMv2 simulator. The simulations are validated against data from a real trade fair.

- **Wal et al. 2017:** Wal et al. analyze the effects of culture, cognition, and emotions on crisis management of individuals. They develop a model, called IMPACT, where the behavior of each agent is based on 30 factors. The factors are subdivided into four categories: individual characteristics, people-people interactions, people-environment interactions and decision-making strategies. Such factors are the speed of an individual or the tendency to help a falling agent. The IMPACT model is based on a BDI-inspired model called ASCRIBE. In contrast to the previous models presented in this section, the authors implemented their model in the NetLogo programming environment (Wilensky 1999). The authors employ simple if-then-else rules where NetLogo takes care of the movement of agents on a cellular grid. The simulations are validated against data from an evacuation drill.

2.3.3 Conclusions on pedestrian stream models including psychology

The multi-agent community proposes numerous models to include intentional, normative, cognitive and neurological factors into agent-based simulations to make them more realistic. They involve numerous parameters and impose architectural complexities (see Fig. 2.29, p. 46). For this reason, these models have not been widely adopted by the pedestrian dynamics community which is mostly interested in the motion of pedestrians. Therefore, the usefulness of these approaches in regard to pedestrian dynamics cannot be assessed fully.

Only a few authors tried to integrate psychological factors into simulation tools with a strong focus on pedestrian dynamics. But so far, no systematic approach exists to combine well-grounded physical locomotion of agents and their mental state to allow behavioral changes of agents which reflect what humans do: perceive the environment, process this information and react appropriately.

2.4 Existing microscopic simulators

As first step, a mathematical and algorithmic pedestrian movement model is derived from real-world observations. A plethora of existing modeling approaches were presented in the previous Sec. 2.3. In a subsequent step, such models are implemented as stand-alone computer programs or as holistic simulators with graphical user interfaces and additional tools to set up scenarios and to analyze simulation results. This section should shed light on existing simulators for microscopic pedestrian movement which could be a starting point for my own implementation.

Several companies offer licenses for commercial crowd simulators based on microscopic models. However, their models are closed source, that is, we do not fully understand how and why individual agents move in the way they do. This hinders comparison between models and thus the knowledge transfer between researchers that I strive for. Therefore, I just want to provide a state-of-the-art list of commercial microscopic pedestrian simulators as overview in the next section Sec. 2.4.1. In Sec. 2.4.2, I present current open-source frameworks in more detail which are suitable as foundation for my own implementation.

2.4.1 Commercial simulators

This overview of commercial simulators is based on an internet research using the Google search engine with the search terms “pedestrian crowd simulation software” on Nov 4, 2020. The goal is to unearth the seven most popular commercial simulators for pedestrian dynamics. In Tab. 2.4, I list the first seven commercial simulators which were found with these search terms.

Simulator name	Company	Programming language
AnyLogic	The AnyLogic Company	Java
MassMotion	Oasys	C++
Pedestrian Dynamics	INCONTROL	C++/Delphi/4DScript
PTV Viswalk	PTV Planung Transport Verkehr	not revealed
SimCrowds	uCrowds	C++
crowd:it	accu:rate	Java
SimWalk	Savannah Simulations	C++

Table 2.4: Seven commercial simulators for microscopic pedestrian dynamics (ordered by their Google search index on Nov 4, 2020).

An up-to-date list of 14 commercial simulators and eleven open-source simulators for agent-based simulations can be found in Richards 2020. The dissertation Sivers 2016 (p. 17–22) provides an exhaustive list of 43 simulators (commercial and open-source ones). Sivers also mentions the main focus of a simulation tool. For instance, “evacuations” or “airports”.

2.4.2 Open-source simulators[4]

The overview in Tab. 2.5 lists frameworks that have been documented through publications or tutorials and have undergone recent development activities. The table shows the initial release date, the programming language the simulator is based on, the number of files and the lines of code [5].

Among the seven simulators in Tab. 2.5, SUMO (simulation of urban mobility) plays a special role. SUMO focuses on complete intermodal traffic systems including road vehicles, public transport and pedestrians, while FDS+Evac, JuPedSim, Menge and MomenTUMv2 concentrate on the actual pedestrian dynamics.

FDS+Evac The Fire Dynamics Simulator (FDS) has been developed by the National Institute of Standards and Technology (NIST) since 2000 (McGrattan et al. 2019). FDS started as a pure large-eddy simulator for slow flows which focuses on smoke and heat

[4]The overview of open-source simulators is taken from Kleinmeier, Zönnchen, et al. 2019, p. 14–16. The publication was a joint cooperation between Benedikt Zönnchen, Marion Gödel, Gerta Köster and me, but the overview reflects my own analysis of existing open-source simulators. Please note, that the GAMA platform was not part of the overview in Kleinmeier, Zönnchen, et al. 2019, p. 14–16.

[5]The lines of code exclude test code, blank lines and comments. The lines were counted with the “cloc” software tool. See appendix 1 for more details about how lines of code were obtained.

Simulator name	Initial release	Programming language	Files	Lines of code
FDS+Evac	2007	Fortran	715	249,702
GAMA	2007	Java	2009	370,957
JuPedSim	2014	C++	774	173,973
Menge	2014	C++	697	67,476
MomenTUMv2	2016	Java	814	56,569
SUMO	2001	C++	1,618	253,472
Vadere	2010	Java	977	73,145

Table 2.5: Open-source simulation frameworks for microscopic pedestrian dynamics (in alphabetical order).

transport from fires. In the following years, the VTT Technical Research Centre of Finland joined this development and integrated the evacuation module FDS+Evac into FDS in 2007. FDS+Evac focuses on simulating human egress situations.

The simulation framework consists of four components: **(1)** The simulation core which is called FDS. **(2)** The graphical user interface Smokeview (SMV) that is used to display the output of FDS. **(3)** The FDS+Evac submodule for FDS to integrate agent-based simulations of humans and **(4)** additional third-party tools for visualization, pre- and post-processing. FDS+Evac uses the social force model (Helbing and Molnár 1995) to move agents in a 2-dimensional plane and offers grouping behavior and different exit selection strategies for agents. FDS+Evac is described in more detail in Korhonen et al. 2007.

GAMA GAMA (GIS Agent-based Modeling Architecture) has been developed since 2007 as an open-source project under the umbrella of the international research collaboration "Unit for Mathematical and Computer Modeling of Complex Systems" (UMMISCO). Five French and two Vietnamese research groups are involved in the development of the GAMA platform. The focus of GAMA lies in carrying out spatially correct simulations with thousands of agents. To this end, GAMA can import several GIS-related (Geographic Information System) data formats. To be able to simulate thousands of agents efficiently, GAMA moves agents using a regular grid or using graph data structures. The agents are programmed with a declarative domain-specific language called GAMA Modeling Language (GAML). In this, GAMA differs from all other simulators in this section where agents are programmed in regular programming languages like Java or C++. The GAMA Modeling Language is supposed to encourage also non-computer scientists to model agent behavior.

The GAMA platform offers an Eclipse-based GUI to model and carry out simulations and to analyze the simulation output. GAMA is built on the Eclipse integrated development environment (IDE) and its plugin architecture. Small and mostly independent plugins are put together to build up the whole simulator. The minimal configuration of GAMA requires five plugins: **(1)** The modeling and simulation core which offers data structures and the simulation kernel to model agent-behavior and to carry out simulations. **(2)** The graphical user interface. **(3)** A plugin to bundle all external libraries to define the GAMA modeling language. Plugin **(3)** to **(5)** are supportive libraries for processing the GAMA modeling language. Additionally, optional plugins exist to cover a wide range of use cases. For instance, plugins to enable communication between agents via the FIPA standard, a physics engine for collision modeling, a plugin to process GIS data, another one to model BDI-aware agents or a plugin to run simulations in a high-performance computing (HPC) environment. GAMA is described in more detail in Taillandier et al. 2017.

JuPedSim JuPedSim's development is mainly driven by the Forschungszentrum Jülich. JuPedSim is a framework for the simulation of pedestrian dynamics at a microscopic level that focuses on evacuation scenarios.

JuPedSim consists of four modules: **(1)** JPScore simulates the movement of agents. JPScore provides three models on the tactical layer: a shortest path strategy, a quickest path strategy and a cognitive map to explore the environment, e. g. to discover doors. On the operational layer, JPScore provides three continuous models based on ordinary differential equations: the force-based generalized centrifugal force model (Chraibi, Seyfried, and Schadschneider 2010), the collision-free velocity model (Tordeux, Chraibi, and Seyfried 2015) and the wall-avoidance model (Graf 2015). **(2)** JPSreport includes tools for density, velocity and flow measurements to analyze agent trajectories. **(3)** JPSvis visualizes simulation results through 2D or 3D animations. JPSvis can be directly connected to JPScore to get an online visualization of a simulation run. **(4)** JPSeditor is a tool for editing model parameters and the topography. JuPedSim is described in more detail in Chraibi and Zhang 2016.

Menge The Menge framework originated at the University of North Carolina. Like for Vadere, the goal is to facilitate model comparison. For this, the Menge developers provide a very generic framework and invite researchers to contribute to the project.

Menge breaks the simulation down into six sub-problems: **(1)** Target selection. **(2)** Plan computation: find the destination by using graphs or potential fields. **(3)** Plan adaption: use local navigation to find the preferred velocity **(4)**. Motion synthesis: this means the physical motion of an agent including head, shoulder and feet movement which is not yet addressed within the Menge framework. **(5)** Environmental queries: identify influencing factors which are in line-of-sight of agent. **(6)** Crowd systems: simulations of aggregated individuals.

Compared to Vadere, Menge offers but also insists on a software structure which realizes all three levels of pedestrian behavior defined in Hoogendoorn and Bovy 2004: the operational (locomotion) layer, the tactical layer, and the strategic layer. This predefined structure is valuable if the model can be mapped onto it but hampering if not. Overhead and additional complexity result in longer development times before a researcher can compare locomotion models. Menge is described in more detail in Curtis, Best, and Manocha 2016.

MomenTUMv2 MomenTUMv2 has been developed at Technical University Munich. The focus lies on analyzing and comparing pedestrian behavior models.

Like Menge, the MomenTUMv2 framework implements all levels of pedestrian behavior defined in Hoogendoorn and Bovy 2004. That is, the simulation as well as the software itself breaks down into strategic, tactical and operational layers. The strategic layer is responsible for the destination choice of agents. The tactical layer contains four items: **(1)** Navigating to a destination **(2)** Participating (e. g. in front of a stage) **(3)** Queuing **(4)** Searching unknown locations. The operational layer provides models for walking and waiting agents. Both models can either use a cellular automaton or a force-based model for locomotion. Compared to Vadere, and similar to Menge, the three-layered structure in the software introduces development overhead before two locomotion models can be compared. MomenTUMv2 is described in more detail in Kielar and Borrmann 2016.

SUMO SUMO is spearheaded by the Institute of Transportation Systems of the German Aerospace Center (DLR). The SUMO simulator allows to evaluate infrastructure changes before implementing them in a real environment. Its scope and its user community are much larger than that of the other pedestrian dynamics simulators. I mention it, because in the long run, an interface between SUMO and well-established locomotion models from the pedestrian community would benefit the scientific community. SUMO is described in more detail in Krajzewicz et al. 2012.

Vadere The Vadere project was started in 2010 (Sivers 2016, p. 23). Its main intention is to facilitate development and comparison of locomotion models. Therefore, it was designed as a generic framework, but with an eye on keeping it lightweight, so that new locomotion models can be quickly implemented.

Vadere's architecture applies the model view controller (MVC) software pattern (Gamma et al. 1994). Therefore, Vadere is divided into three interconnected modules: `state`, `gui` and `simulator`. Moreover, Vadere is complemented by two supporting modules: `utils` and `meshing`. In sum, it is composed of five separated modules. The MVC pattern leads to a clear separation of responsibilities for the three MVC modules within Vadere:

- Model (`state`): the model layer does not contain any logic. Instead, it is the simulation state, that is, the composition of agents, sources, obstacles, targets and their corresponding attributes like the x and y coordinate of an agent.
- Controller (`simulator`): the control layer contains the logic to change objects of the model layer. For instance, to update the x and y coordinate of all agents in each time step. Mainly, the control layer holds implementations for different locomotion models.
- View (`gui`): the view visualizes the current state of the model objects in form of a GUI. The optional GUI supports setting up simulation scenarios, simulating them and analyzing the output. Simulations can also be carried out without the GUI by using the command-line interface of Vadere.

Vadere is described in more detail in Kleinmeier, Zönnchen, et al. 2019.

2.5 Validation of pedestrian dynamic models

In the last two sections, I provided an overview of important models for pedestrian stream simulations. First, these models are usually derived by real-world observations. Then, these models are implemented and embedded in a simulation software which were presented in the previous section. In this last section, I scrutinize how pedestrian stream models can be validated. Validation is an important step in a reliable modeling pipeline. Validation ensures that a model is able to replicate real-world observations so that it can finally be used for predictions. In the validation step, simulation results of a model are checked against real-world data.

2.5.1 Validation of locomotion models

Visual validation Already in 1986, Gipps dedicated a paper to stress the importance of graphical techniques to validate simulation models (Gipps 1986). Gipps is right when he states that it is difficult and time-consuming to detect (modeling) errors in tables of numbers. It is more useful to visualize these tables. For instance, if the table contains trajectory information, one can graphically visualize the positions over time for all agents to easier detect flaws and glitches. The human brain can immediately recognize if agents overlap or collide with walls which would indicate a modeling or implementation error. Therefore, visual validation is a quick and easy technique in the development phase of new models to detect errors. Of course, visual validation also depends on subjective views of the person who looks at the data. This makes visual validation not the first choice for validation but a useful step in the validation phase.

Validation against trajectories and fundamental diagrams Visual validation is a manual task. Therefore, one also requires methods to validate thousands of simulation runs quickly. Different metrics exist to compare pedestrian streams on a microscopic level. For instance, two trajectories could be compared directly (position by position over time). Yet, trajectories are an error-prone quantity because they differ in each scenario. E. g. queuing behavior of humans at a ticket counter leads to small steps while walking in an unobstructed corridor leads to larger steps. Therefore, usually more robust quantities are used for validating simulation results. Such quantities are fundamental diagrams for different scenarios like **(1)** unidirectional flows (e. g. experiments by Hankin and Wright 1958; Weidmann 1993; Daamen 2004; Jelić et al. 2012), **(2)** bidirectional flows (e. g. experiments by Zhang, Klingsch, Schadschneider, et al. 2012; Zhang, Schadschneider, and Seyfried 2014), **(3)** bottlenecks (Seyfried et al. 2010) or **(4)** staircases (Burghardt, Seyfried, and Klingsch 2013). The publications above are often used by modelers to test if the model is able to replicate the empirically observed speed-density relationship.

Two other useful metrics were proposed by Webster and Amos 2020 to compare simulated and real crowds: "polarization" and the "nearest-neighbor distance" (NDD). The polarization ϕ measures the level of "order" in a crowd, in terms of heading alignment of members. The polarization ϕ is zero when the crowd is completely disordered. That is, everyone is heading in different directions. The polarization ϕ is 1 when all crowd members share the same heading, see Eq. 2.25 (Webster and Amos 2020, p. 6).

$$\phi = \frac{1}{N} \left| \sum_{j=1}^{N} e^{i\theta_j} \right|, \tag{2.25}$$

where N is the total number of crowd members, $|\cdot|$ denotes the Euclidean norm, i denotes the imaginary number and θ_j is the heading of each individual j.

The nearest-neighbor distance (NDD) measures the level of clustering in a crowd by looking at the closest neighbor of each individual crowd member, see Eq. 2.26 (Webster and Amos 2020, p. 6).

$$nnd = \frac{1}{N} \sum_{j=1}^{N} d_j, \tag{2.26}$$

where N is the total number of crowd members and d_j is the Euclidean distance between an individual pedestrian j and its closest neighbor. Small values represent denser crowds while high values indicate a loosely coupled crowd.

Empirical data serves another two important topics: it can help to identify model parameters during the model development phase and to identify the range of parameters for simulations (parameter estimation).

Experiments as basis for empirical data An important basis of empirical observations are carefully conducted experiments. In the last decade, we observe an upsurge in the published literature about pedestrian dynamics. For instance, Haghani 2020 presents experimental data from 194 experiments from 2005 to 2019 in his exhaustive literature review. These experiments can be categorized into **(1)** laboratory condition experiments, **(2)** virtual/augmented reality (VR/AR) experiments and **(3)** evacuation drill experiments. Also animal experiments are considered by the review but these experiments are not useful for validating pedestrian stream models. Laboratory experiments are a useful resource to collect quantitative but also qualitative data. Since 2005, different experiments were carried out by numerous researchers. The experiments can be clustered into following topics (Haghani 2020, p. 12–16):

- Single-file movement of pedestrians
- Unidirectional flow
- Stepping behavior of pedestrians
- Directional flows under the rhythm effect
- Multi-directional flows of pedestrians
- Conflict/collision avoidance in bidirectional pedestrian flows
- Conflict/collision avoidance in multi-directional pedestrian flows
- Merging flows of pedestrians
- Pedestrian flows through bottlenecks
- Pedestrian flows at bottlenecks and architectural adjustments
- Fundamental diagram of pedestrian flows
- Pedestrian boarding and alighting behavior
- New measurement methods (e.g. pressure sensors)
- Social group behavior
- Limited visibility conditions
- Pedestrians with limited mobility

Extracting useful quantities for validation is a time-consuming task. Most often, the positions over time of experiment participants are extracted. Either manually or in an automatic process. An automatic process is often only possible if the participants have worn colored markers during the experiment. In the past, more and more microscopic locomotion models were successfully validated against fundamental diagrams from Weidmann 1993 or other experiments. E. g., a modified version of the social force model was validated against an egress scenario with 600 people (Parisi, Gilman, and Moldovan 2009). An optimal reciprocal collision avoidance model was validated against an evacuation drill experiment (Poulos et al. 2018). The optimal steps model was validated against a corridor scenario (Seitz and Köster 2012).

The Forschungszentrum Jülich builds up a central database for experiments focused on pedestrian dynamics. Each experiment is described textually and with pictures and is assigned with a unique document object identifier (DOI), compare Fig. 2.30. The experiment data is usually provided as trajectory file for each participant. The database is called “Pedestrian Dynamics Data Archive” which is described in Boltes, Holl, and Seyfried 2020 and can be found at: https://ped.fz-juelich.de/da/

Figure 2.30: Snapshots of experiments found in the “Pedestrian Dynamics Data Archive” provided by the Forschungszentrum Jülich. From first column to last column: bottlenecks, uni- and bidirectional flow and different crossings (snapshots were taken from the Pedestrian Dynamics Data Archive at https://ped.fz-juelich.de/da/).

The guideline for microscopic evacuation analysis Another useful resource to validate simulation results is the “Guideline for Microscopic Evacuation Analysis” (RiMEA 2016). In its latest revision from 2016, the guideline establishes standardized criteria which should be applied when using computer simulations to determine the evacuation time of humans in specific scenarios. To this end, the guideline defines certain scenarios (the topography with walls, doors, stairs etc.), expected evacuation times (within a margin) and expected evacuation routes for a given number of participants.

2.5.2 Validation of psychology-inspired models

The experiments from the previous section mostly focus on providing quantitative data. In such experiments, participants often have clear instructions to perform a single task. But, psychological aspects are often neglected. Possible causes are that psychological aspects are often only expressed qualitatively by questionnaires about emotions or verbal descriptions. For researchers and modelers, who have not conducted the experiment themselves it is almost impossible to extract psychological aspects because the exact experiment setup is not known in detail including the mental state and any priming of the participants. Therefore, validating models including psychological aspects impose special challenges. Relevant qualitative data must be extracted from fuzzy, human descriptions or derived from a time-consuming video analysis focusing on human behavior. Therefore, the psychology-inspired models from Sec. 2.3.2 were mostly validated qualitatively. This qualitatively-only validation is definitely a scientific gap when dealing with psychology-related pedestrian dynamics models.

2.5.3 Uncertainty quantification as systematic methodology to identify uncertainties

Even if a quantitative validation is not possible under certain circumstances, uncertainty quantification (UQ) offers a possibility to quantify the uncertainty of introduced model parameters. The central question we ask is: do model parameters have a great impact on quantities of the simulation output? UQ tackles this problem by varying input parameters and check the effect on chosen output quantities, see Fig. 2.31. UQ is a relatively new research area within probability and statistics (Smith 2014, p. ix) which is used for several applications: from mechanical engineering, over fluid dynamics to pedestrian dynamics (Najm 2009; Hu and Mahadevan 2017; Gödel, Fischer, and Köster 2020).

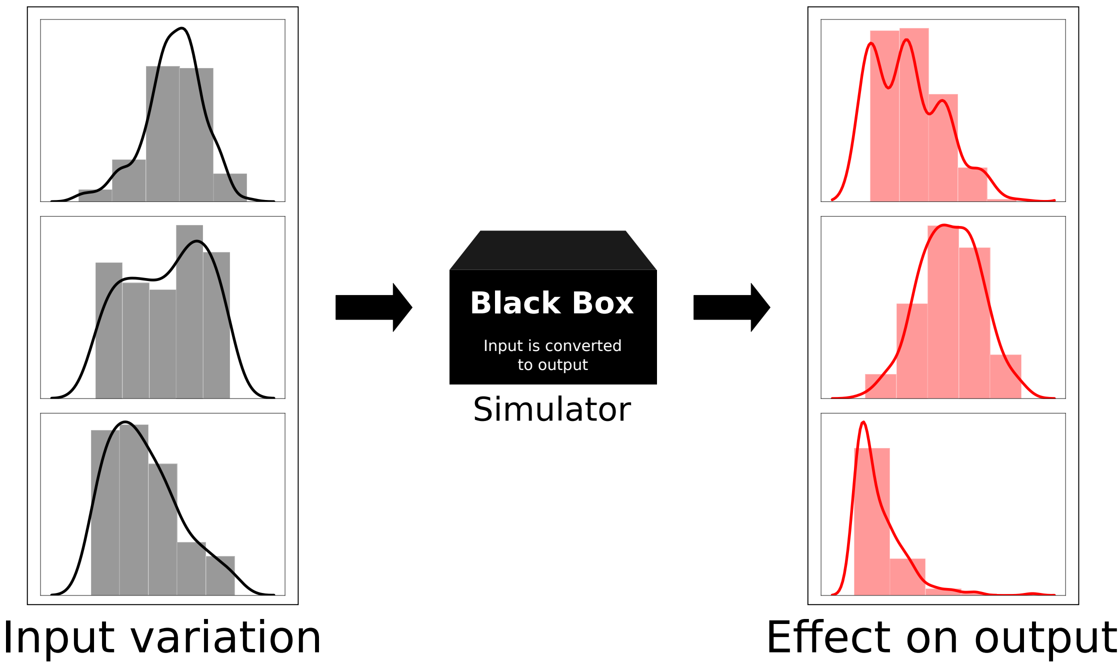


Figure 2.31: The scientific field of uncertainty quantification (UQ) offers systematic approaches to measure the uncertainty and the impact of model parameters on the simulation output.

2.6 Summary

At this point, most models for pedestrian dynamics solely focus on locomotion of simulated agents but neglect psychological aspects in crowd motion. These physics-inspired locomotion models can be categorized by their scale: macroscopic, mesoscopic and microscopic models. Macroscopic locomotion models do not distinguish individuals. The system dynamics over time are described using aggregate quantities, such as densities or flows. In contrast, microscopic locomotion models focus on the locomotion of individuals by using dedicated equations and algorithms to replicate accurate stepping behavior of pedestrians. Mesoscopic models are set between the macroscopic and the microscopic level. In mesoscopic models, agents are considered as individuals — with individual properties like preferred speed — but their motion is described as an aggregated relationship. Since microscopic models focus on individuals, this model type is the preferred one to integrate my psychological findings.

There are only a few pedestrian dynamic models that also consider psychological aspects when maneuvering agents through virtual environments. Such models take the nearby environment of an agent into account by perception components, an agent's mental state and aspects like stress levels or helping behavior when an agent has fallen down.

All of the presented models are implemented, either as standalone program or within an existing simulation framework. I shortly reviewed existing simulators. For the commercial ones, I limited the overview to a short list of seven simulators because the unpublished code hinders the scientific knowledge transfer. Therefore, I will use an established open-source simulation framework to integrate my new model for behavioral changes in agent-based simulations. I reviewed seven open-source simulators, namely FDS+Evac, GAMA, JuPedSim, Menge, MomenTUMv2, SUMO and Vadere. My preferred choice is Vadere because it was designed from the ground up as framework to compare locomotion models. For this reason, Vadere is already packaged with different carefully validated locomotion models like the optimal steps model.

Finally, each model should be validated against empirical data to test the usefulness of the model. I shed light on different validation techniques, namely visual validation and data-driven validation based on trajectories and fundamental diagrams. Additionally, I proposed uncertainty quantification as a method to quantify the uncertainty of introduced model parameters.

Chapter 3 The psychology of human decision-making

In this section, I would like to distill which aspects influence human decision-making and can have an effect on pedestrian streams. I will analyze which of these findings can be systematically integrated in a computer simulation model for pedestrian dynamics to allow realistic behavioral changes of agents. The great challenge is to extract the relevant aspects which could influence human pedestrian streams from the broad research field of psychology. For this reason, this section is rather based on textbook knowledge than latest journal articles (as in the last section) because a textbook provides a broader overview of the huge research topic of psychology. Nevertheless, the knowledge is also backed up and underpinned by peer-reviewed journal articles where appropriate. I chose Gerrig 2013 which is used as introductory textbook for psychology students. The version that I cite was authored by Richard Gerrig only, a professor of psychology at Stony Brook University, New York.

Former editions were co-authored by Philip Zimbardo. Zimbardo is an American professor emeritus of psychology at Stanford University who became well-known for his “Stanford prison experiment”. Zimbardo recruited 24 young men to participate in a study on prison life where the participants were randomly assigned as guards or prisoners. The study was terminated prematurely because guards repressed the prisoners and their cruelty escalated. The experiment was heavily criticized because of ethical and methodological mistakes and its scientific validity is questionable (Haslam, Reicher, and Van Bavel 2019). For instance, Zimbardo announced the objectives of the experiment to the guards during the orientation day (Le Texier 2019, p. 5). Additionally, the experimenters gave clear instructions to the guards instead of just observing the scene (Le Texier 2019, p. 5).

The “Stanford prison experiment” exemplifies the difficulty of conducting psychological experiments very well. But, even if Zimbardo’s “Stanford prison experiment” was discredited in the scientific community, the introductory textbook (Gerrig 2013) provides a good overview of psychology, its research branches, research methods and conducted experiments. The book shows how different psychological hypotheses were tested in the past. Therefore, the readers are informed well and they can decide — based on experimental studies —- if they trust in a psychological hypothesis or not. In psychology, humans — or animals in a broader context — are the object of investigation. In contrast to physical materials, all humans have their own personalities, their own traits and specific behavior which stems from them. Therefore, psychological conclusions about humans and their behavior are hard to draw even if applying scientific methods carefully.

The main focus of this dissertation is to show how psychological aspects that affect human behavior and pedestrian streams can be systematically integrated in a computer simulation model for pedestrian dynamics. Therefore, this chapter mostly addresses readers with a computer science background and not psychologists which already have a comprehensive education in that field. As stated before, the challenge is to extract relevant factors which influence pedestrian streams and find a common ground for the computer model which suites for different simulation scenarios (e. g., evacuations, commuting situations, demonstrations and so on).

3.1 Introduction

The American psychology professor Richard Gerrig defines "psychology as the scientific study of the behavior of individuals and their mental processes. [...] The goals of the psychologist conducting basic research are to describe, explain, predict, and control behavior." (Gerrig 2013, p. 2–3) For this reason, psychologists usually follow four steps to draw conclusions:

1. Describe what happens: that is, obtain data and make accurate observations about behavior.
2. Explain what happens: find explanations for the observed behavior. This goes beyond the pure observations.
3. Predict what will happen: these are statements about the likelihood of a specific behavior in a given context. For example, if your parents are vegetarians, how likely is it that you are also a vegetarian?
4. Control what happens: make a specific behavior happen or prevent one.

In the broad field of psychology, there are different perspectives to understand behavior: the psychodynamic, behaviorist, humanistic, cognitive, biological, evolutionary and sociocultural perspective. Tab. 3.1 summarizes the seven perspectives on psychology defined by Gerrig 2013, p. 6. Each perspective defines own causes and consequences of behavior. Nevertheless, each perspective contributes to the understanding of human and animal behavior with own research methods and techniques. For instance, the biological perspective heavily focuses on visualizing brain activity and the activity of nerve cells by using sophisticated electronic devices. On the other hand, the sociocultural perspective uses questionnaires, surveys, narrative notes, police reports and newspaper articles to formalize the interplay between different social groups.

3.2 Perception: From physical events to mental events

A definition of perception One important factor which influences human behavior is the perception of the environment. For instance, if we approach a red traffic light when driving a vehicle, we stop. The term perception refers to the process of apprehending

Perspective	Focus of study	Primary research topics
Psychodynamic	Unconscious drives, conflicts	Behavior as overt expression of unconscious motives
Behaviorist	Specific overt responses	Behavior and its stimulus causes and consequences
Humanistic	Human experience and potentials	Life patterns, values, goals
Cognitive	Mental processes, language	Inferred mental processes through behavioral indicators
Biological	Brain and nervous system processes	Biochemical basis of behavior and mental processes
Evolutionary	Evolved psychological adaptations	Mental mechanisms in terms of evolved adaptive functions
Sociocultural	Cross-cultural patterns of attitudes and behaviors	Universal and culture-specific aspects of human experience

Table 3.1: The seven perspectives on psychology defined by Gerrig (table: Gerrig 2013, p. 6).

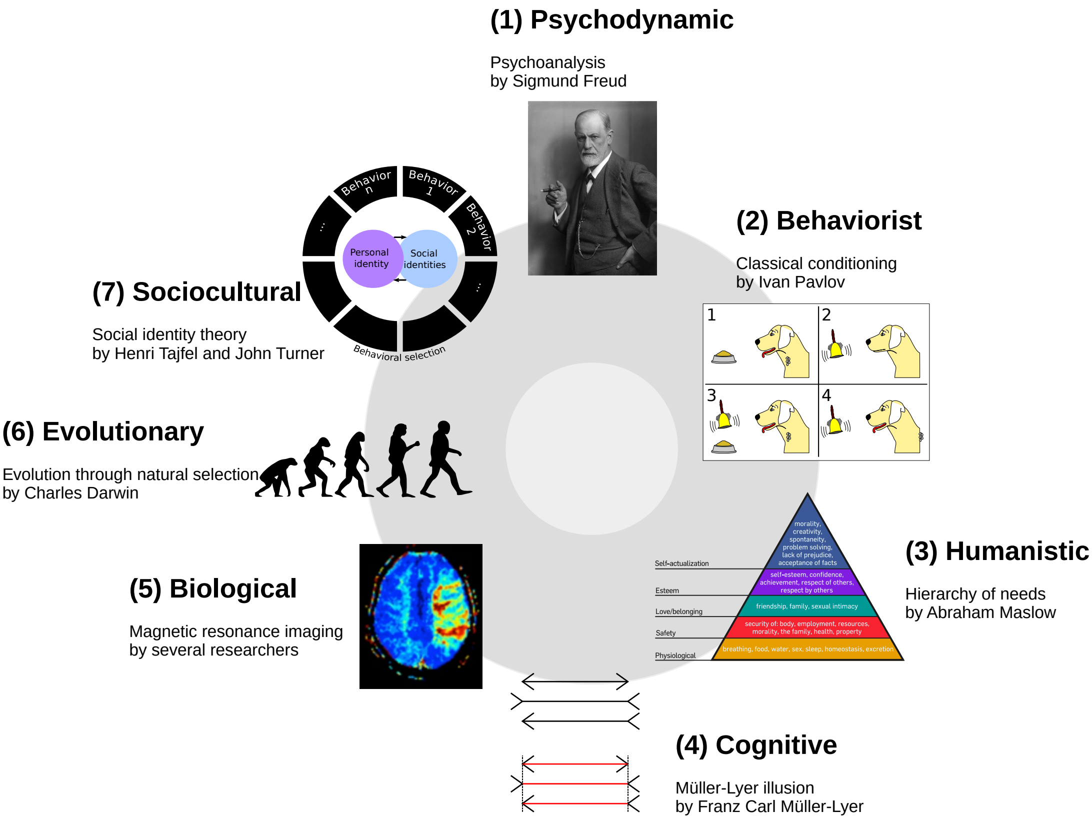


Figure 3.1: Examples of important findings of the seven psychology perspectives (own graphic but image (1) of Sigmund Freud by Max Halberstadt, 1921, the images (1) to (5) from Wikimedia Commons 2020).

objects and events in the environment. For psychologists, perception encompasses to sense objects and events, understand, recognize and label them and also to prepare a reaction (Gerrig 2013, p. 80), which is also visualized in Fig. 3.2.

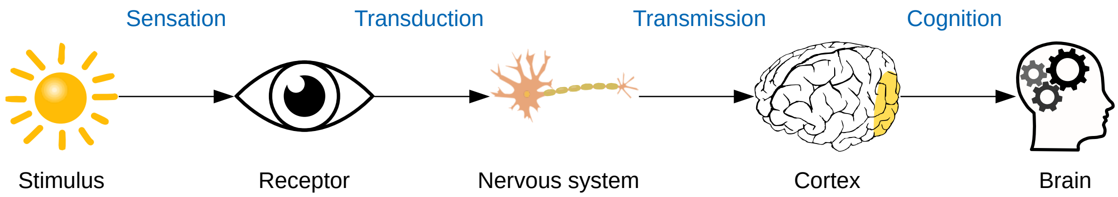


Figure 3.2: The actors (black) and processes (blue) involved in the human perception process (own graphic but sun, neuron and brain icon from Free SVG 2020).

The functions of perception: Survival and sensuality Perception mainly serves two functions (Gibson 1962): firstly, the process of perception ensures our survival. Humans and animals can smell food and perception allows us to recognize dangerous situations, e. g. a fire. Secondly, perception brings us joy and satisfaction, e. g. the sweet taste or smell of a cake. The second function is summarized as sensuality which also denotes the intensity and quality of the perception.

Perception as three-step process: Sensation, perceptual organization and identification Perception can be broken down into three sequential processes (Gerrig 2013, p. 80): sensation, perceptual organization and identification. Sensation covers the physical detection using sensory receptors (e. g., eyes and ears), the transformation of physical signals into neural impulses which are passed to the brain. During the perceptual organization, the brain integrates all sensory input and compares it with existing knowledge of the world. This integration covers an object's size, shape or movement for example. In the identification process the questions "What is the perceived object?" and "What is its function?" are answered. This is called recognition. Fig. 3.3 visualizes the three-step process of perception consisting of sensation, perceptual organization and identification. In a later step, all the perceptional impressions are processed actively by a cognition process.

Distal and proximal stimuli Psychologists distinguish between distal and proximal stimuli (Graham 1992, p. 55–56). The distal stimulus describes a real object in the world while the proximal stimulus reflects the projection of the same object on an observer's retina in case of visual perception. Both representations differ enormously. In case of visual perception, an object in the real world is three-dimensional, but its projection on the retina is two-dimensional. Our brain is able to interpret this projection as 3D object. All human senses — hearing, smelling, tasting etc. — involve a distal and proximal processing. The process of perception transforms a distal stimulus in a proximal stimulus. The distinction between distal and proximal stimuli is a good example that mathematical models for computer simulations must simplify the real world. Psychologists strongly emphasize the distinction between distal and proximal stimuli. But, from a modeling perspective this discrimination can be neglected for a pedestrian stream

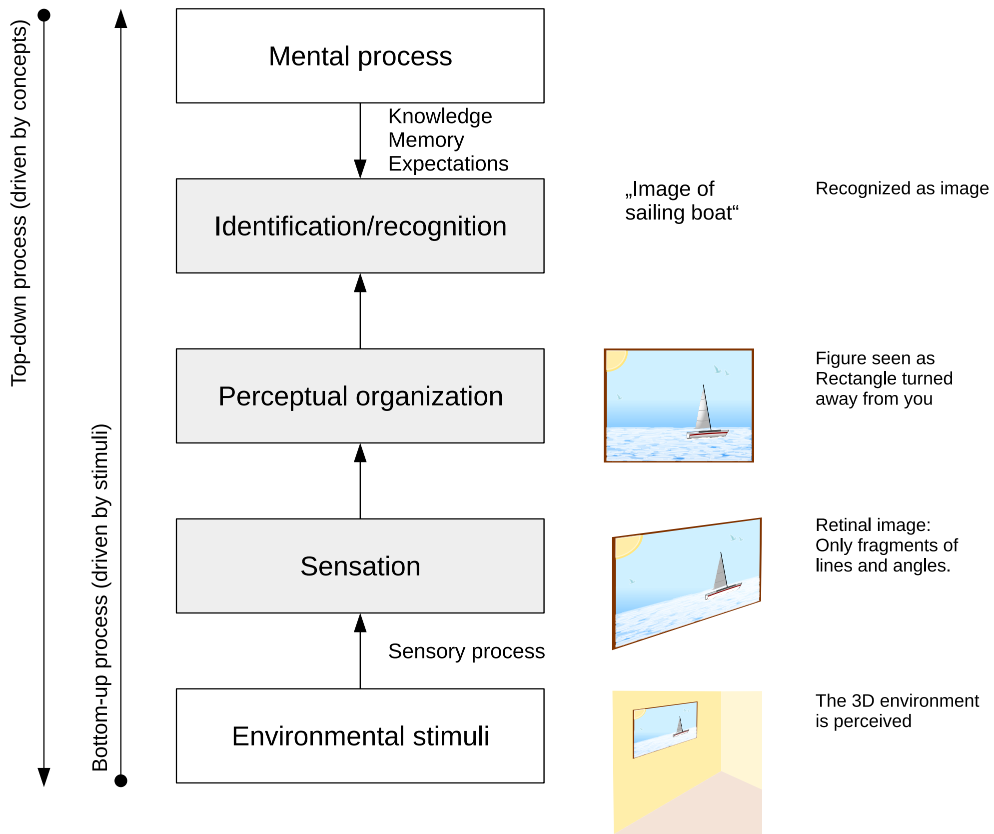


Figure 3.3: Perception as three-step process defined by Gerrig 2013, p. 82: sensation, perceptual organization and identification. Perception can be seen as bottom-up approach where the environmental stimulus triggers the perception. On the other hand, our existing knowledge about the world influences our perception, especially the identification step, which can be seen as top-down approach (own graphic but inspired by: Gerrig 2013, p. 82).

model. Modelers simplify this process by abstraction since the transformation from distal into proximal stimulus does not influence human motion. Instead, we are interested in the final result of this process, that is, the decision a person makes. Nevertheless, the general concept of perception is an important one that should be picked up by modelers.

Psychophysics A central research domain when talking about perception is psychophysics. Psychophysics is the study of the relationship between physical stimuli and the following mental experience or response (Gescheider 1997, p. ix). In psychophysics, systematic studies are carried out to reveal which physical intensity is necessary so that a stimulus can be detected by humans. For instance, how loud must an alarm be in an emergency case? In this context, the absolute threshold is defined as the "minimum amount of physical energy needed to produce a sensory experience" (Gerrig 2013, p. 82). To this end, researchers perform detection tasks with participants were the intensity of a stimulus is varied continuously. Usually, there is no clear threshold that separates undetected stimuli from those that humans detect. Therefore, the absolute threshold takes this into account and defines the stimulus level at which a sensory signal is detected half the time (by participants). When plotting the stimulus intensity on the horizontal axis and the detection rate on the vertical axis, the graph is a S-shaped sigmoid curve, see Fig. 3.4. First systematic studies in psychophysics date back to the German physicist Gustav Fechner (1801–1887). From a modeling perspective this means, that environmental stimuli should have a certain intensity. For instance, this intensity level limits the radius in which a stimulus can be perceived.

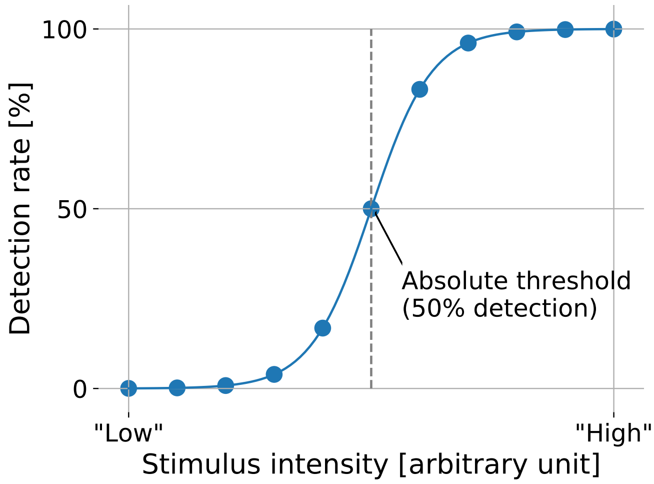


Figure 3.4: The detection rate in psychophysics when participants are exposed to a physical stimulus: the absolute threshold is the stimulus level at which a sensory signal is detected half the time.

When talking about the absolute threshold and detection of physical stimuli, it is also important to note that the human perception is more sensitive to detect changes in the environment than observing steady state conditions. This has naturally evolved by the process of sensory adaption which describes the diminishing responsiveness of sensors to a continuous stimulus (Gerrig 2013, p. 83). For instance, when moving from a dark room into a bright sunny scene, first, the human eyes are blinded by the bright light but over time the pupil gets smaller and the eyes are not blinded anymore. Sensory adaption allows humans to quickly react to environmental changes. The perception of stimuli — or signals in general — is closely connected to the signal detection theory in psychophysics which is covered in more detail in (Green and Swets 1966).

From physical events to mental events Before closing this section with an overview of human senses, it is also important to describe the information flow from physical to mental events. What happens when humans sense physical energy in form of light or sound? All physical energy in the environment is detected by human sensory receptors. The energy is converted into neural (electrochemical) impulses. The conversion from one form of energy into another is called transduction. All environmental stimuli are converted to identical neural impulses. Thus, each sensory input (e. g., seeing) is processed in a first step in a dedicated brain region that is part of the cerebral cortex (Courten-Myers 1999, p. 219). For instance, the visual cortex processes information from the eyes. This allows humans to distinguish different stimuli sources. That is, the human sensory system shares the same basic flow of information from sensory receptors to dedicated brain regions via the nervous system.

The human senses To detect physical stimuli, humans are equipped with different sensory receptors which are summarized in Tab. 3.2. The visual and the hearing system are more developed than other sensual systems like smelling. They are primarily used to guide humans through the environment. Animals have additional receptors for sensing more physical stimuli than listed in Tab. 3.2. For example, pigeons can detect magnetic fields (Leask 1977).

Sense	Receptor	Sensation
Vision	Eyes	Color, brightness
Hearing	Ears	Frequency, loudness, timbre
Smell	Nose	Odorant molecules
Taste	Mouth	Sweet, sour, bitter, salty, umami
Touch	Skin	Pressure, warmth, cold
Vestibular sense	Inner ear	Orientation, balance
Kinesthetic senses	In muscles	Feedback about motor activities
Pain	Fine meshgrid covering entire body	Temperature, mechanical stimuli, chemicals and others

Table 3.2: The humans senses and its corresponding sensory receptors.

3.3 Cognition: Mental processes

A definition of cognition "Cognition is any mental activity involved in the representation and processing of knowledge, such as thinking, remembering, perceiving, and language use" (Gerrig 2013, p. 167). The definition states that cognition involves both, the content and its processing: the content we perceive and that we store in our memory or which we retrieve from our memory; the processing describes how we manipulate this content. That is, how we interpret this content, how it shapes our personality and how we solve problems in our daily life. Fig. 3.5 depicts some inputs which are used in a cognitive process by the human brain. Cognition has evolved to an autonomous and interdisciplinary academic field in the last decades covering aspects from philosophy, neuroscience (brain science), linguistics, cognitive psychology, computer science (AI) and other fields.

Mental processes take time One old but omnipresent finding from the Dutch cognitive psychologist Franciscus Cornelis Donders (1818–1889) is that each mental activity takes time (Greenwood 1999, p. 19; Goldstein 2011, p. 6–7). Donders scientifically measured the speed of mental processes by conducting a reaction time experiment in 1868, see Fig. 3.6. Donders was interested in how long it takes for a person to make decisions and chose the following experimental setup. In the first part of the experiment, the participants were asked to press a button upon recognizing a light. The measured time was called "simple reaction time". In the second part of the experiment, Donders made the task more difficult. He presented two lights, one to the left and another one to the right. Donders asked the participants to push button A when the left light was illuminated and button B when the right light was illuminated. The measured time was called

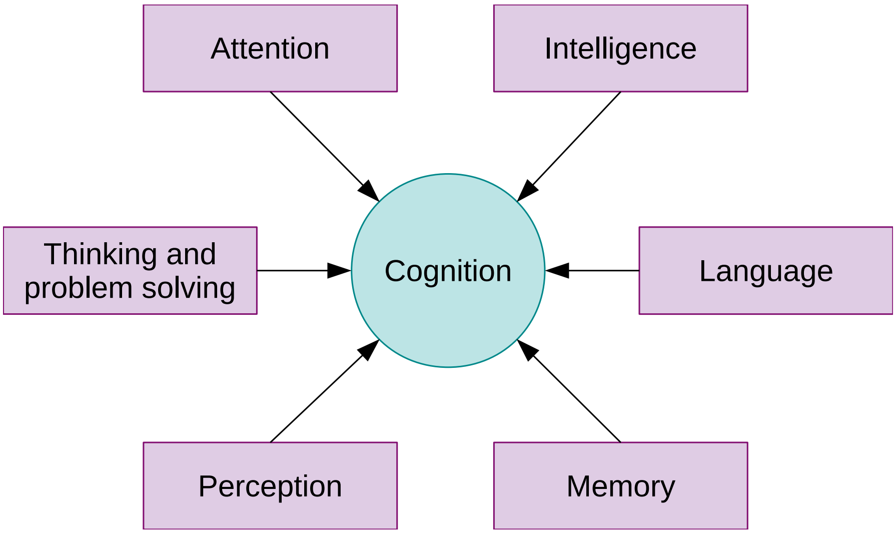


Figure 3.5: Different inputs for the cognitive process of humans. First, you have to direct attention to a specific task. Then, humans use different capabilities to process a task (own graphic but inspired by: Gerrig 2013, p. 207).

"choice reaction time". In the first part of the experiment, only the reaction time to a stimulus was measured. In the second part of the experiment, the time measurement also included a mental response (push button A or B). Donders revealed in this simple task that the "choice reaction time" was one-tenth of a second longer than the "simple reaction time" (Goldstein 2011, p. 7). That is, the more demanding a mental task is, the more time it takes to process the task. For each task, one has to direct attention to it and then process different inputs (language, memory, perception) by using intelligence and thinking capabilities. Donders pioneered the work on cognitive processes because he realized that mental processes could not be directly measured at that time but must be deduced from behavioral reaction times (Goldstein 2011, p. 7).

The different inputs attention, intelligence, language, memory and thinking are not described in this work because they are not of greatest importance for modeling pedestrian streams. The interested reader should consult (Gerrig 2013) where each input is discussed in an own chapter or section. More important from a modeling perspective is that humans process information from different sources, merge them in a cognitive process and make decisions based on this processing (e. g., press button A or B).

Mental processes: Serial versus parallel, controlled versus automatic Psychologists distinguish serial and parallel cognitive processes (Li et al. 2020, p. 1–2). While serial processes are carried out in order, parallel processes can be carried out simultaneously. Talking and walking are examples for parallel processes whereas walking and painting usually cannot be performed in parallel. A further distinction are controlled and automatic processes (Shiffrin and Schneider 1977). Controlled processes require attention and are usually performed sequentially. Automatic processes on the other hand do not require attention.

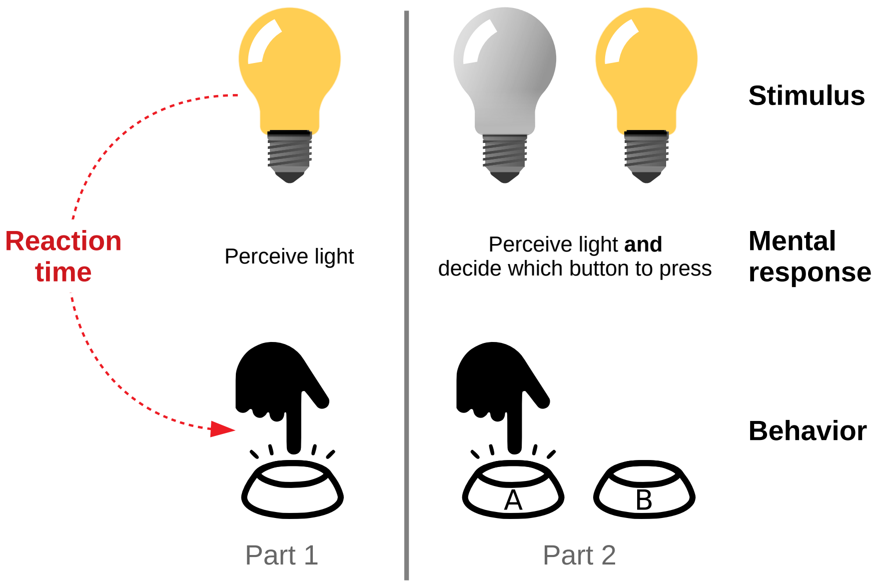


Figure 3.6: The Dutch psychologist Franciscus Cornelis Donders (1818–1889) measured the time of mental processes by using elaborated experiment setups. In a first step, Donders measured the time for a simple response task (left). In a second step, Donders measured the time for a discrimination response task (right). From his experiments, Donders concluded that each mental process takes time and more difficult tasks require more time than easier tasks.

Cognitive influences on learning Learning is also a cognitive process which is based on experiences and affects the future behavior or behavioral potential. A simple example is when touching a hot cooktop for the very first time. The painful experience prevents us from repeating the action. Such learning aspects are mostly studied under the behaviorism perspective of psychology. Experiments with animals and humans revealed three important cognitive effects on learning:

1. Cognitive maps: humans and animals use spatial memory to plan their route through environment (Gerrig 2013, p. 167). For instance, squirrels bury food in autumn and recover it during the winter season by using a cognitive map.

2. Habituation versus sensitization: habituation means that responses to stimuli get less intense over time, when the stimuli occur repeatedly. Sensitization means that responses to stimuli become stronger, when the stimuli occur repeatedly. Sensitization is more likely to stimuli which are irritating.

3. Observational learning: humans learn and imitate behavior by observing others. This is also known as “social learning” and was studied by Bandura, Ross, and Ross 1963. In this famous study, children, aged from 35 to 69 months where exposed to aggressive role models who punched a doll. These children were more likely to also punch the doll than a control group of children who were not exposed to aggressive role models.

3.4 Behavior: Motivational aspects and decision-making

After processing inputs in a cognitive phase, humans derive an action from it, a behavior. Such a behavior is driven by motivation or the social context (which is introduced in Sec. 4).

Motivation Motivation is “the process of starting, directing, and maintaining physical and psychological activities” (Gerrig 2013, p. 298). Psychologists differ between three sources of motivation: drives and incentives, instinctive behaviors and learning, expectations and cognitive approaches (Gerrig 2013, p. 299–301).

Drives are internal triggers of humans and animals which are fired when the physiological needs are in disequilibrium, hunger for example. Drives were already addressed by pedestrian dynamics modelers. For instance, Wijermans modeled festivalgoers that go to the toilet from time to time by introducing a “bladder” parameter (Wijermans 2011). Additionally to drives, incentives affect the motivation of humans. In contrast to drives, incentives are external triggers. Imagine a bus driver bringing kids to school even if he or she is hungry because he/she gets paid for driving.

Instinctual behaviors, like straightening of the fur of many animals in dangerous situations, can also influence future activities. Researches in the 1900th century suggested that many human activities are driven by instincts (James 1905, p. 403 ff.). Pedestrian dynamics modelers used this instinctive view to justify the modeling of “panic behavior” (Helbing, Farkas, and Vicsek 2000; Pelechano, Allbeck, and Badler 2007; Bellomo, Piccoli, and Tosin 2012). Yet, newer researches suggest that humans rather rely on learning aspects than on instinctive behaviors (Bateson and Mameli 2007). For instance, when we drive a car and we come close to a red traffic light, we stop which is a learned behavior and not an instinctive reflex. The psychologist Sime asked the provocative question “Escape Behaviour in Fires: ‘Panic’ or Affiliation?” in his dissertation (Sime 1984). Sime challenged the irrational or “instinctive” behavior of humans in “panic” situations: “For shorthand this is called the panic concept or scenario. Evidence of real behaviour in fires does not support it. As will be shown, people appear to behave rationally in the light of the information they have.” (Sime 1984, p. 3 in PDF file). There are more reasonable and more scientific explanations to describe human behavior in extreme situations than the fuzzy word “panic”. And modelers must take this newer explanations into account. To this end, Sec. 4 also includes the social context — how humans act in social groups — which also affects the behavior in extreme situations. For instance, the psychologists Drury, Cocking, and Reicher found that in emergencies, victims helped each other instead of fleeing chaotically as the word “panic” suggests (Drury, Cocking, and Reicher 2009a).

Expectations and cognitive approaches are the third source which motivates humans — it is not only physiology or only instincts. The social psychologist Festinger proposed in his cognitive dissonance theory that humans are driven by the discrepancy (dissonance) between beliefs and reality which leads to “corrective behaviors” to bring both in harmony (Festinger 1957). For example a cognitive dissonance arises, when a smoker gets aware of risks associated with tobacco use.

Problem solving, reasoning and decision-making Problem solving and reasoning combine current information and information from the memory to achieve a specific goal. There is an information gap between the initial state and the end state. This gap is closed by the process of problem solving. In this context, psychologists use the terminology problem space and algorithm (Simon and Newell 1971; Newell and Simon 1972).

The problem space are "the elements that make up a problem: the initial state, the incomplete information or unsatisfactory conditions the person starts with; the goal state, the set of information or state the person wishes to achieve; and the set of operations, the steps the person takes to move from the initial state to the goal state" (Gerrig 2013, p. 224). An algorithm describes a step-by-step procedure to solve a given problem.

To reveal mental processes, psychologists carry out experiments and use "think-aloud protocols" to yield an exact description of how test persons solve problems. While algorithms can easily be integrated in existing pedestrian stream simulations another aspect of problem solving cannot: creativity, that is, the ability to generate novel ideas. This is one of the objectives the artificial intelligence community strives for.

In 1979, Kahneman and Tversky pioneered the work on decision-making, the process of choosing between alternatives. Kahneman and Tversky argue that people's judgments often rely on heuristics instead of taking all available options into account because the human brain has limited processing resources. They claim that *fast and frugal* heuristics often lead to correct judgments. Tversky and Kahneman identified three fundamental heuristics which are used in the human decision-making process: **(1)** availability, **(2)** representativeness and **(3)** anchoring (Tversky and Kahneman 1974).

The availability heuristic refers to the fact that humans use information readily available in mind instead of starting a long thinking process. The representativeness heuristics leads people to making decisions based on a few averaged impressions instead of taking the sum of all impressions. For instance, a music concert is often rated by people using the peak intensity and the intensity at the end (Gerrig 2013, p. 232). The anchoring heuristic means that a judgment depends on the original starting value. This heuristic is best explained using an example. Guess within 5 seconds the following results:

a) $1 \cdot 2 \cdot 3 \cdot 4 \cdot 5 \cdot 6 \cdot 7 \cdot 8 =$ __________

b) $8 \cdot 7 \cdot 6 \cdot 5 \cdot 4 \cdot 3 \cdot 2 \cdot 1 =$ __________

Tversky and Kahneman 1974, p. 1128 showed that the median estimate for the first, ascending sequence was 512, while the median estimate for the second, descending sequence was 2,250 and the correct answer is 40,320. Humans rely on the very first "anchors" they perceive. Pedestrian modelers like Seitz, Bode, and Köster successfully used a heuristic approach to steer agents through virtual environments (Seitz, Bode, and Köster 2016) instead of utilizing all information which would be available in a simulation model. For instance, when carrying out a specific simulation step, the positions of all agents are globally known and could be "injected" into an agent to select the next "optimal" step. Instead, the authors use an heuristic approach where agents only use local information and their direct neighborhood to derive the next footstep.

3.5 Summary and impact on agent-based simulations

This chapter shed light on human behavior from a psychological perspective. Psychologists' goals are to describe, explain, predict, and control behavior. For this, psychologists conduct experiments with human or animal subjects. Psychology tries to explain behavior from different perspectives: namely, psychodynamic, behaviorist, humanistic, cognitive, biological, evolutionary and sociocultural perspective. Each perspective involves a wide variety of research methods and tools.

From a modeling perspective, the challenge in this section was to identify psychological aspects that influence pedestrian streams and to find a common ground which suites different simulation scenarios. Psychologists identify two important processes which mainly influence the human behavior: perception and cognition. Humans perceive their environment, process this input and adapt their behavior accordingly. The process of perception includes the sensation of physical stimuli by receptors (e. g. eyes), the conversion from physical impulses to electrochemical impulses which are transmitted by the nervous system to the brain. In a second process stage, the cognition, humans process the input further, think about the input and enrich it with further information to solve problems.

Each human activity is driven by some kind of motivation. Psychologists identify three sources of motivation: drives and incentives, instinctive behaviors and learning, expectations and cognitive approaches.

As described in Sec. 2, current modeling approaches for pedestrian dynamics mostly focus on physically correct simulations but neglect psychological aspects when navigating agents. That is, locomotion modeling and psychology have been treated as isolated worlds so far. On the one hand, locomotion modelers usually do not have a broad and well-grounded knowledge of important psychological foundations about influences on human decision-making. On the other hand, psychologists usually do not have the necessary knowledge to derive a mathematically correct model, implement it accurately and verify the implementation by systematic tests. It is my aim to close this gap with this dissertation — at least a bit. In this section, I worked out and emphasized that the human (and also animal) decision-making process starts with the perception of the environment. In a subsequent cognition phase the perceptional input is processed and enriched with existing knowledge. This is a well-grounded theory which was developed by psychologists and must be the connection point for agent-based models and locomotion modelers. Thus, the perception and cognition aspect must be picked up later when modeling behavioral changes of agents for simulations in Part II. The challenge will be to integrate these findings but not making the model too complex. Besides perception and cognition, the social context influences the behavior of humans. Therefore, we will have a closer look at social influences in the next chapter.

Chapter

4 The social psychological perspective: From classical crowd psychology to modern views

So far, I have provided an overview of existing locomotion models for pedestrian stream simulations and of those that are suitable to integrate psychological aspects. Additionally, I presented psychological factors which influence the decision-making processes of humans. One factor is still missing: how do humans behave in a social context with other humans and how does this influence their behavior? After formulating a verbal model, I will derive a simple and reusable architecture which encompasses those aspects allowing more realistic simulations which are presented in Sec. 6.

Social groups and crowds The objects of investigation of social psychology are individuals and groups. Social psychologists study how personality, attitudes, motivations, and behavior of individuals are influenced by social groups and the presence of others.[1]

In natural sciences, we are accustomed to having clear and unambiguous definitions of phenomena and facts. For instance, the function $f(x)$ with input x is defined as $f(x) = x^2$ for $x \in \mathbb{R}^2$. Contrarily, in social psychology often multiple definitions exist for the same phenomenon. For instance, Challenger et al. 2009, p. 59 list seven possibilities to define a "crowd". Therefore, I need to decide which one to use. I refer to the following definitions for four key terms which are frequently used within social psychology:

- **Social group:** "A social group can be defined as two or more individuals who share a common social identification of themselves" (Tajfel 1982, p. 15). For example, two football supporters form a social group when visiting a game of their favorite football team.
- **Crowd:** "A compact gathering or collection of people with connotations of homogeneity of characteristics and unanimity of behavior" (Brown and Lewis 1998, p. 649.). For example, many shoppers at a Christmas market can form a crowd.
- **Crowding:** "Situations of close physical proximity" (Novelli 2010, p. 23). For example, commuters standing in the subway are described by the term crowding.

[1] Merriam-Webster. (n.d.). Social psychology. In Merriam-Webster.com dictionary. Retrieved November 23, 2020, from https://www.merriam-webster.com/dictionary/social%20psychology.

- **Collective actions:** "Collective action consists of people's acting together in pursuit of common interests" (Tilly 1977, p. 11). For example, protesters at a demonstration who block the police carry out a collective action.

Current researchers of crowds and crowd behavior emphasize the distinction between a physical crowd — a gathering of people in the same location, but each with their own personality — and a psychological crowd — an aggregate of people who are united by common social identity and shared goals (Reicher and Drury 2010, p. 162; Reicher 2011, p. 3; Templeton, Drury, and Philippides 2015, p. 1).

(a) Physical crowd: commuters on the New York City subway, 2017 (image: Robert Nickelsberg/Getty Images)

(b) Psychological crowd: pope Francis greets a crowd at St. Peter's Square in Rome, 2016 (image: GC/Pacific Press/Barcroft Images).

Figure 4.1: The adverse and pleasurable effects of crowds and crowding which are stressed by modern social psychologists contradict classical crowd psychology views. In **(a)**, commuters ignore each other by standing back to back and looking at their smartphones. In **(b)**, the people share their emotions. They laugh and wave their hands together to greet pope Francis.

Crowd researchers also stress the adverse and pleasurable effects of crowds and crowding, see Fig. 4.1. For instance, while commuters feel stressed in an overcrowded subway, people standing together as dense crowd to greet the pope feel positive emotions because of their close proximity. That is, similar physical densities lead to completely different feelings and behaviors. This is contrary to what classical crowd psychologists in the 20th century suggested, where crowds were seen as inherently "mindless" and violent (Le Bon 1895). Therefore, it is important to include such findings in modern computer models for crowd simulations.

In the following two sections, I draw a picture from classical crowd psychology starting in the 19th century to modern views of crowds and their behavior. Fig. 4.2 depicts influential social psychologists in that era.

4.1 Classical crowd psychology

Gustave Le Bon (1841–1931): Group mind theory (1895) In Europe, "crowd science" arose in the late 19th century in France as a response to social problems of urbanization and unrest (Nye 1975). It was an attempt to understand these social problems. At that time, industrialization evolved quickly and numerous workers came from the villages to live in the cities. Industrialization also meant that workers organized in unions and

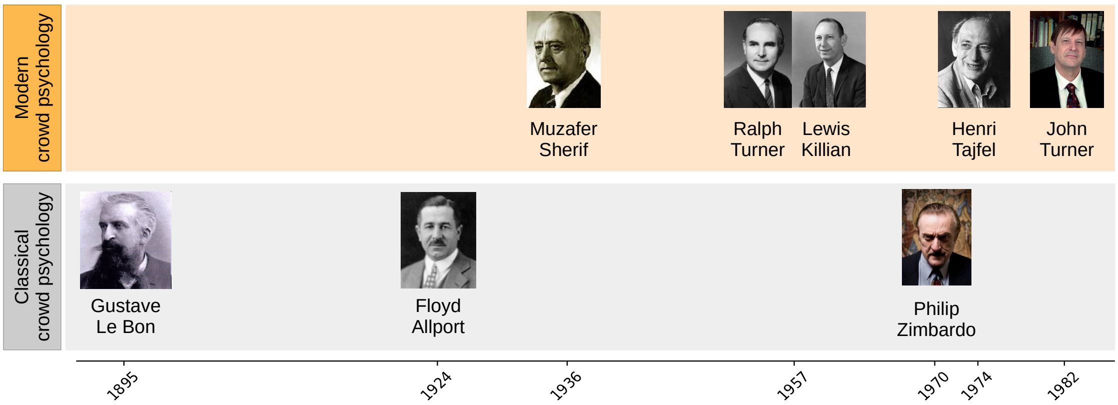


Figure 4.2: Timeline of influential social psychologists (portraits taken from Drury 2019a; Drury 2019b).

strikes arose. At that time, Le Bon summarized his observations about crowds in (Le Bon 1895). But instead of providing an unprejudiced view on crowds, Le Bon expresses the concerns of the establishment at that time. People who gather as crowd are perceived as a public threat (for the establishment): "Isolated, he [a man] may be a cultivated individual; in a crowd, he is a barbarian..." and finally "...a crowd puts them [individuals] in possession of a sort of collective mind..." (Le Bon 1895, p. 13 and 11). Le Bon argues that the anonymity in the crowd leads to a disappearance of the individual personality (a loss of self). Then, the crowd behavior is governed by a group mind which is driven by primitive instincts. Le Bon emphasizes that contagion reinforces the group mind effect. Le Bon's view on crowds is very one-dimensional. The group-mind theory cannot explain peaceful gatherings and how crowd members interact and influence each other.

Floyd Allport (1890–1979) Individualism theory (1924) Like Le Bon, Allport wanted to explain inherent crowd violence as Le Bon. But, Allport rejected Le Bon's idea of a single group mind in crowds. Instead, Allport argues that the individual is the proper unit when analyzing crowds. Allport concludes that individual (violent) predispositions (innate and learned ones) lead to crowd violence and suppress civilized values that normally control crowd behavior (Drury 2019a, p. 22). Stimulation by other co-present individuals reinforces the effect of crowd behavior.

Philip Zimbardo (1933): De-individuation theory (1969) Zimbardo conducted experiments like the "Stanford prison experiment" (Zimbardo 1999) in which participants are embedded in a setup of arousal, group presence and anonymity. In his debatable experiments (see Sec. 3.1, p. 59), Zimbardo observed "a sudden change in the restraints which normally control the expression of our drives, impulses, emotions [...] Behaviour is freed from obligations, liabilities, and the restrictions imposed by guilt, shame, and fear" (Zimbardo 1969, p. 248) which lead to counter-normative behavior in Zimbardo's eyes. A meta-analysis of 60 publications by Postmes and Spears showed little evidence that anti-normative behavior results from de-individuation (Postmes and Spears 1998). Instead, the authors found a strong relation to conformity. That is, test persons in de-individuation experiments tried to fulfill "their tasks" as well as possible.

Summary on classical crowd psychology While Le Bon claims that crowds are inherently violent, Allport argues that individuals in the crowd control the group mind. Zimbardo argues that group presence and anonymity reduce self-control and lead to a state of de-individuation with impulsive and irrational behavior. All these classical theories neglect that most crowds are peaceful. All these theories do not take the personal motives of the crowd members (mostly protesters at that era) into account. Therefore, these theories are decontextualized. Thus, modern views onto crowd behavior are required which can explain violent crowds but also peaceful gatherings. Consequently, it is not advisable to include the older, one-dimensional theories of crowd behavior into modern models to simulate pedestrian dynamics.

4.2 Modern crowd psychology

Muzafer Sherif (1906–1988): Psychology of social norms (1936) Instead of claiming that crowds are inherently violent, like classical crowd psychologists proposed, Sherif has a more differentiated view on crowds and gatherings. In his book *The psychology of social norms*, Sherif writes: “When a group of individuals faces a new unstable situation and has no previously established interests or opinions regarding the situation, the result is not chaos; a common norm arises and the situation is structured in relation to the common norm” (Sherif 1936, p. 111). Sherif draws this conclusion after conducting an experiment where participants were situated in a dark room and they watched a moving light, once individually and once in a group (Sherif 1936, p. 89–113). The participants estimated the distance the light moved during the experiment, first alone and afterwards in a group situation. The experiment revealed a significant convergence of individual’s judgments to the group median which indicates an internalization of the group estimate (a “group norm”). The addition of social norms is an important contribution to social psychology and a break with former crowd psychology.

Ralph Turner (1919–2014) and Lewis Killian (1919–2010): Emergent norm theory (1957) Turner and Killian applied Sherif’s idea of social norms to crowd events. In Turner and Killian 1957, they described a more formalized four-step process to explain collective behavior — violent and non-violent: **(1)** An incident triggers the process, for instance disasters or social conflicts. **(2)** The trigger marks the break from everyday norms. **(3)** Then, the interaction between the participants starts to obtain a guide of conduct for the new situation. **(4)** Eventually, a norm emerges which gets shared by the participants. Turner and Killian stress that collective behavior is norm-governed and the emergent norm theory is able to explain violent but also non-violent crowd behavior. This theory marks a first step towards a model which could be implemented as algorithm because of its clearly defined steps. The previous theories were too fuzzy in this sense.

Henri Tajfel (1919–1982) and John Turner (1947–2011): Social identity theory (1974) and self-categorization theory (1987) The social psychologists Tajfel and Turner took up emergent norm theory and addressed one key issue that is attached with the emergent norm theory: is a long-running, interpersonal interaction always required before collective action can occur? The social psychologist Reicher showed in a detailed analysis about the St. Pauls riot in Bristol, 1980, that no long interaction process is necessary to carry out collective actions (Reicher 1984). Shortly after the police arrested a cafe owner in his cafe — because of allegations of illegal drinking and the sale of drugs — citizens of the St. Pauls district crowded together and fought against the police without a long milling process. In Tajfel 1974, Tajfel introduced three key ideas to better understand these collective actions (when do they occur?) and behavioral changes in crowds (how do they look like?):

- Humans have multiple identities: personal and social identities. For instance, a man with a child is a “father” when being at home. But when being in a football stadium, the same man is a football supporter with all the corresponding attitudes (e. g. shouting and singing loudly, drinking beer etc.).
- Crowd behavior arises by a shift in salience from personal to a shared social identity. That is, the members of a crowd share an identity (e. g., football supporter) and adopt its norms (e. g., sing loudly).
- A social identity is defined in relation to other groups. Humans distinguish between in- and out-group members. Members of the same group (in-group members) are treated differently than out-group members. This was colorfully shown in a recent study presented in (Novelli, Drury, and Reicher 2010). Novelli, Drury, and Reicher showed that in-group members keep a smaller personal space to each other than to out-group members. Another current experiment supports the different treatment of in- and out-group members. In (Templeton, Drury, and Philippides 2018), the authors compared the behavior of physical and psychological crowd members: in comparison to the physical crowd members (out-group), members of the psychological crowd (in-group) walked slower, walked further, and maintained closer proximity. The same authors concluded in Templeton and Neville 2020b, p. 36: “the categorisation of people as ingroup or outgroup members is important for modelling collective movement in crowds [...]”.

Besides having multiple social identities (e. g., father and football supporter), there is another important process from the social psychology perspective which should be taken into account when modeling behavioral changes of agents. In (Turner, Hogg, et al. 1987), the authors introduce the process of self-categorization as an essential aspect of collective behavior. The authors conclude that humans categorize themselves into categories (identities) to which they belong to when coming together in a social context and they apply the norms of this category. This self-categorization process allows humans to change categories which leads to behavioral changes of crowds by following new (social/categorial) norms.

Modern social psychologists subsume the social identity theory and the self-categorization theory under the umbrella term “social identity approach” (Reicher, Spears, and Haslam 2010). The usefulness and versatility of the social identity approach for explaining crowd behavior and behavioral changes have been shown by several authors in the last years. For instance, Drury, Cocking, and Reicher 2009a used the social identity approach to accurately describe human behavior in emergencies instead of hiding the observed crowd behavior behind fuzzy words like “panic” or “irrationality” which were used by classical crowd psychologists. Other researchers used the social identity approach to accurately describe crowd behavior in different situations (Reicher 1984;

Haslam, Holme, et al. 2008; Drury, Cocking, and Reicher 2009b; Alnabulsi and Drury 2014; Templeton, Drury, and Philippides 2018).

Introducing multiple identities, norms and self-categorization is an important and very concrete step towards operationalization of collective actions and behavioral changes of crowds which can be implemented as computer model for simulations. All these aspects tackle limitations and inconsistencies of previous crowd psychology theories. Newer approaches allow to explain violent but also non-violent crowd behavior and will be the basis of my own implementation.

Summary on modern crowd psychology In his pioneering experiment in 1936, Muzafer Sherif observed that norms are established in groups. This idea was extended by Ralph Turner and Lewes Killian to the more evolved emergent norm theory for crowding events in 1957. A long interaction process between crowd members eventually leads to a shared norm. This was identified as major limitation of the emergent norm theory and the social psychologists Henri Tajfel and John Turner addressed this by introducing multiple social identities, norms and self-categorization. These three aspects cover a wider range of collective behaviors — violent and non-violent — than classical crowd psychology views allowed for.

4.3 Summary

While classical crowd psychologists stress that crowds are inherently violent (Le Bon, Allport, Zimbardo), modern crowd psychologists have a more differentiated view on crowds (Sherif, Turner and Killian, Tajfel and Turner). Their goal is to explain both, violent but also peaceful crowding events. The classical crowd psychology view was mainly driven by influential French psychologist Gustave Le Bon at the end of the 19th century. He argued that crowd behavior is governed by a group mind which is driven by primitive instincts and a loss of self. In the 20th century, social psychologists questioned this one-dimensional view on crowds, conducted several experiments and analyzed several crowd events (violent and non-violent ones) which dispose of Le Bon's assertions. In 1936, Muzafer Sherif observed that norms are established in groups and that group members act according to that norms. Other social psychologists drew upon the idea of norms. Ralph Turner and Lewes Killian developed the emergent norm theory which focuses on a long interaction process between crowd members. Henri Tajfel and John Turner observed that there is not always a long interaction process necessary for collective actions of humans. Therefore, they introduced the key concept of multiple social identities, norms and self-categorization as central aspects for collective actions and behavioral changes. Not only they are more valid, but also they are easier to map to a clean software architecture for behavioral changes contrary to classical views on crowd psychology. Tab. 4.1 summarizes the social psychology approaches to explain crowd behavior which were covered in this chapter.

Theory founder	**View**	**Explain crowd behavior by...**
Le Bon 1895	Classical	Group mind theory
Allport 1924	Classical	Individualism theory
Zimbardo 1969	Classical	De-individuation theory
Sherif 1936	Modern	Social norms
Turner and Killian 1957	Modern	Emergent norm theory
Tajfel 1974	Modern	Social identity theory
Turner, Hogg, et al. 1987	Modern	Self-categorization theory

Table 4.1: The different approaches of several social psychologists to explain crowd behavior.

Part II

Operationalization of behavioral changes in simulations

In the first part of this dissertation, I provided an overview of state-of-the-art approaches to model pedestrian streams. Mostly, these models let agents walk from sources to targets while avoiding obstacles and other agents. In the first part, I also shed light on findings from psychology which affect human decision-making and which can trigger behavioral changes. These findings cover perceptional, cognitive and social aspects.

The current part of the dissertation addresses the research question:

> **Research question**
>
> How can changes in human behavior be operationalized for simulations?

In the overview of the state of the art, I worked out that there is no universally accepted locomotion model in the pedestrian dynamics research community. This motivates me to establish an universal approach to allow behavioral changes of agents which can be used in conjunction with different microscopic locomotion models. I also identified different psychological implications that affect the behavior of humans. Now, I will use this knowledge to derive a model for behavioral changes of agents which is **(1)** reusable, **(2)** easy to understand from a conceptual point of view and **(3)** follows the KISS (keep it simple, stupid) principle during its implementation (Martin 2008, p. 10). As visualized in Fig. 1.5 on p. 5, pedestrian dynamics is an interdisciplinary research topic attracting researchers from natural and life sciences. Thus, I strive for a model which is easy to understand for both communities and a wide range of researchers. A simple and slim structure allows to add new findings to my implementation.

First, I will outline the technological foundations for my modeling efforts. Then, I will explain in detail how I model behavioral changes of agents. In a last step, I will show the usefulness of the new model by reenacting three real-world scenarios which are also used to validate my model mostly qualitatively but also quantitatively.

Chapter 5 Model requirements and technological foundation for implementation

This chapter outlines the requirements of my model for behavioral changes of agents and the technological foundation I base my implementation on. Additionally, I demonstrate how I ensure a correct implementation by employing several code quality measures.

5.1 Requirements

I will implement my new model in an established simulator to carry out simulations in the end. By using an established simulator I have sustainability in mind. As simulator, I choose Vadere which has a strong community and which has features like a graphical user interface that make it convenient to use. Thus, implementing my model within its frame enhances chances that it will be used by third parties. A ready-to-use implementation allows researchers **(1)** to set up own scenarios quickly and **(2)** to validate simulation results without undue effort. The implementation step additionally shows that the model is not only a vague, verbal description but can be precisely described mathematically and algorithmically and is a useful step towards more realistic crowd simulations.

As with every software project, it is useful to explicitly write down the requirements in the first place. Clearly stated requirements keep the development process focused, define acceptance criteria for the final "product" and facilitate decisions for the right (software) design (Balzert 2009). I define the functional and non-functional requirements (denoted by F and NF) for my model of behavioral changes and its implementation as follows:

F1: Use an established open-source simulator.
Reason: The locomotion layer must not be re-implemented. It must be open source because scientific work should be transparent and accessible for everyone. An open and royalty-free implementation has better chances that the model will help others.

F2: Use a well-validated locomotion layer.
Reason: The goal is to get valid simulation results.

F3: The model architecture should fit for several simulators.
Reason: Currently, there is a wide range of simulators and simulation frameworks

available. Researchers should be able to easily incorporate my model in other reasonably designed simulators.

F4: Write unit tests for the implementation.
Reason: Each implementation must be verified automatically because each line of code is a potential error.

F5: Provide a GUI to quickly check simulation results and behavioral changes of agents.
Reason: As stressed in (Gipps 1986), graphical techniques are an effective tool to detect faults in computer models. Especially, when modeling psychological aspects where it is difficult to quantify effects of behavioral changes.

NF6: Apply the KISS (keep it simple, stupid) principle.
Reason: The new model should be understandable for different researchers from natural and life sciences, especially psychologists and computer scientists.

NF7: Use accepted psychological theories for behavioral changes.
Reason: Draw upon latest scientific findings and not outdated knowledge (classical versus modern views on crowds, see Sec. 4.3, p. 75).

5.2 Vadere: An open-source framework for pedestrian dynamics

Vadere: Open source, well-validated locomotion models and a ready-to-use GUI To lower the development effort and not to reinvent the wheel, I will base my implementation on an established open-source simulator. As worked out in Sec. 2.2.3, microscopic pedestrian stream simulations suit best to integrate psychological aspects. In Sec. 2.4, I presented seven open-source simulators with recent development activities (FDS+Evac, GAMA, JuPedSim, Menge, MomenTUMv2, SUMO and Vadere). I choose Vadere for my implementation because it was designed from the ground as a framework to compare different locomotion models. It is packaged with implementations of several locomotion models (social force model, optimal steps model, gradient navigation model and others) which were carefully validated. Especially, the optimal steps model was validated in two dissertations (Seitz 2016, p. 65–76, p. 89–91; Seer 2015, p. 39–45) and other publications (Seitz and Köster 2012, p. 5–6; Sivers and Köster 2015, p. 112–114). Additionally, Vadere offers a ready-to-use graphical user interface which allows quick, visual validation of simulation results, see Fig. 5.1.

Vadere's architecture Vadere uses four topography elements to model pedestrian streams: sources, targets, obstacles and agents. Agents are created (or spawned) in sources. After spawning, agents walk to a target while avoiding obstacles and other agents which is achieved by using a specific locomotion model which updates the agents' positions in each simulation step. One simulation step is visualized in Fig. 5.2 showing all the basic modeling components.

Vadere is implemented in the Java programming language by applying the model-view-controller software design pattern, which is also depicted in Fig. 5.3:

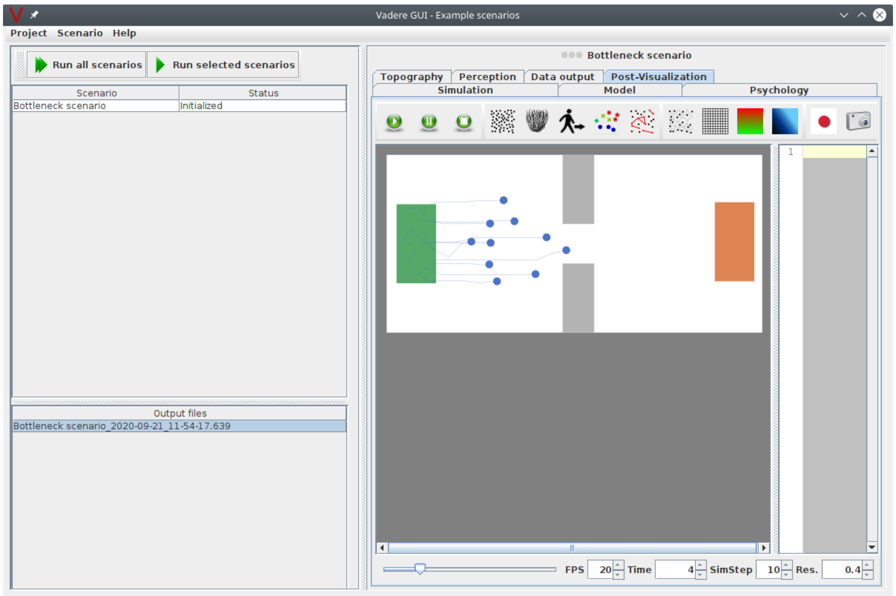


Figure 5.1: The Vadere GUI helps to create, run and analyze simulation scenarios. Left-hand side: the top-panel lists input scenario files, the bottom-panel output files. Right-hand side: the GUI includes a toolbar to create scenarios, which consist of sources, targets, obstacles and agents. Below the toolbar, a canvas visualizes the current simulation state when a simulation is running.

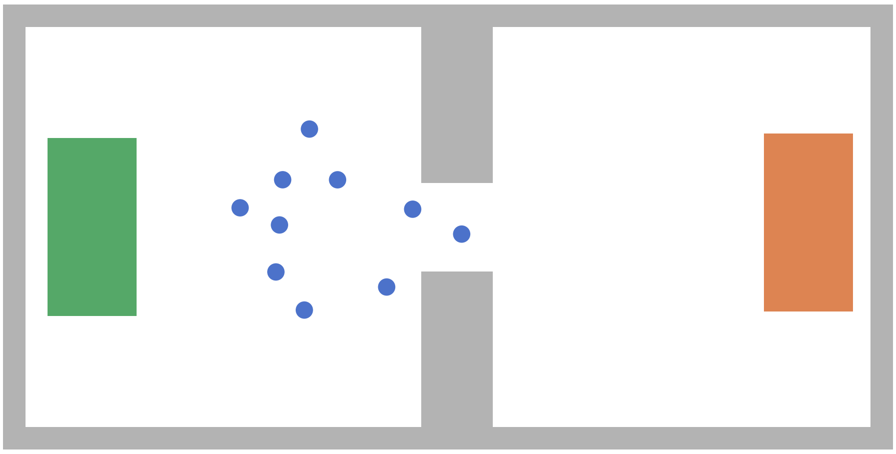


Figure 5.2: The basic modeling components for a pedestrian stream in Vadere. Agents (in blue), are spawned in source areas (green). After spawning, agents walk to target areas (orange), while avoiding obstacles (gray) and other agents.

- **Model:** the basic topography elements like sources and targets are implemented as model classes. A model class just holds information and data about a specific element, e. g. for sources, the geometric shape and the number of agents to spawn.
- **Controller:** each model class has a corresponding controller class to update the model class. For instance, the `SourceController` spawns the requested number of agents in each simulation step.

- **View:** the graphical user interface (which uses Java's Swing library) visualizes the model classes in each simulation step.

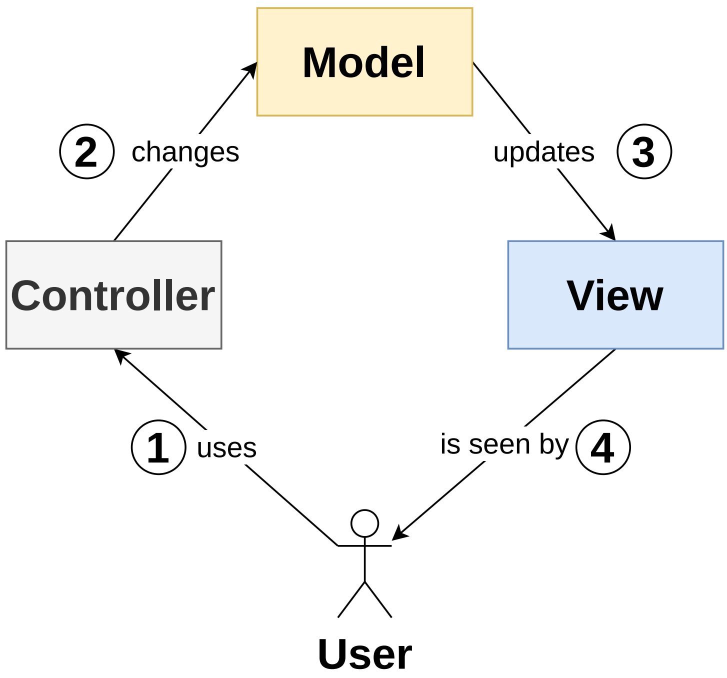


Figure 5.3: The model-view-controller software design pattern which is adopted by Vadere: a user updates the model via the controller which is visualized by the view.

In summary, Vadere consists of five software packages with several classes in each package: `gui` (= view), `simulator` (= controller), `state` (= model), `meshing` and `utils`. The `utils` package contains helper classes for input/output operations and geometric calculations, e. g. writing output files and calculating intersections of two geometric shapes. The `controller` package also contains so called "output processors" which can be used to log data in each simulation step. Besides the position of each agent, additional information can be logged, e. g. the speed of each agent. The `meshing` package provides classes and methods for mesh generation and for solving the eikonal equation during floor field generation, see Sec. 2.2.3 for details. Fig. 5.4 summarizes all important packages and classes of the Vadere simulator.

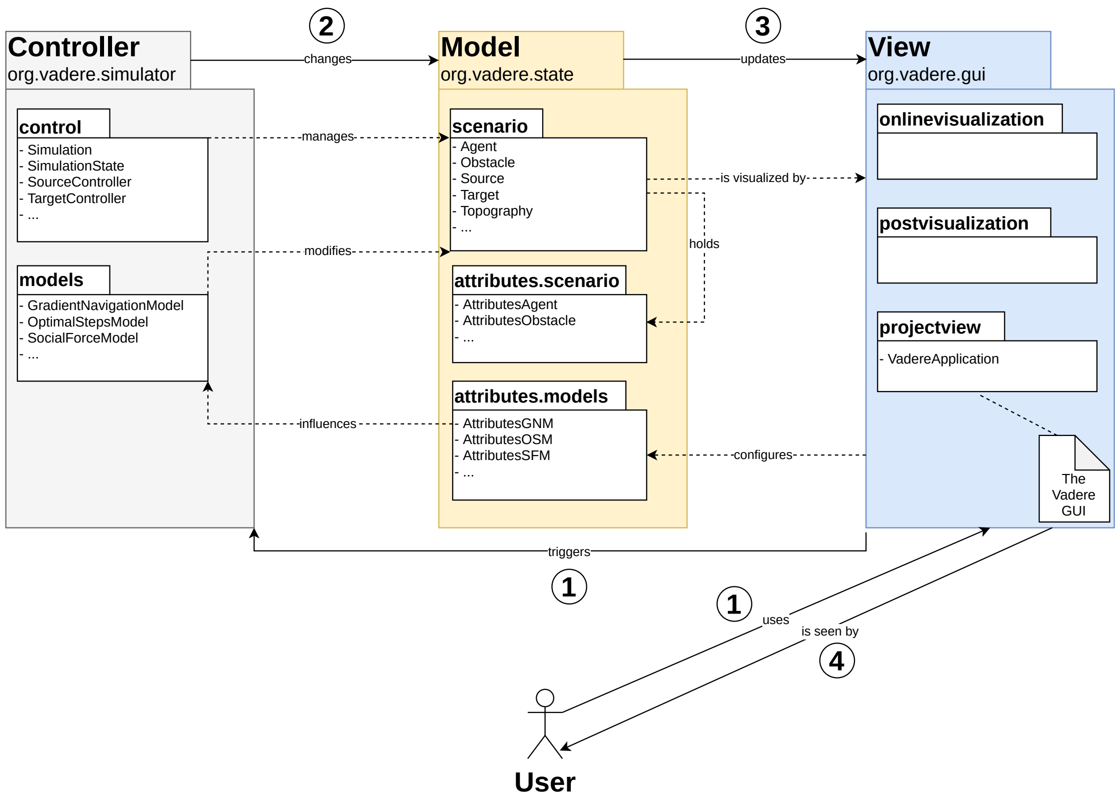


Figure 5.4: Important classes and packages of the Vadere simulator and their interaction (own graphic but inspired by: Kleinmeier, Zönnchen, et al. 2019, p. 19).

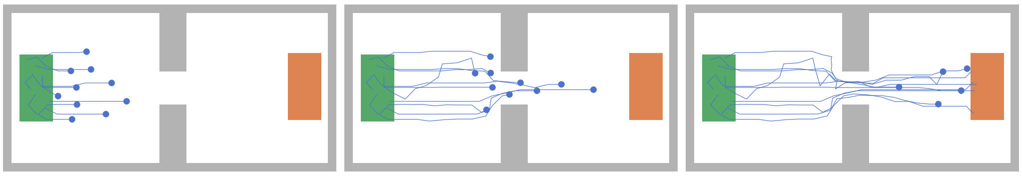
Vadere's simulation loop Vadere's core is its simulation loop — like for any other simulation software. In each simulation step, a locomotion model updates the agents' positions and then a time variable is incremented, see List. 5.1.

Listing 5.1: Vadere's simulation loop: a locomotion model is responsible for updating the positions of agents in each simulation step. Then, the simulation time is incremented.

```
while (simulationIsRunning) {
  ...
  // A locomotion model searches the next
  // position for an agent which is closer
  // to a target than currently.
  locomotionModel.update(agents, time);
  ...
  time++;
}
```

Fig. 5.5 visualizes three simulation steps of the simulation loop (List. 5.1) in which the optimal steps model updates the agents' positions.

Vadere has been designed as a framework to compare different locomotion models. Therefore, each locomotion model must implement an interface. The generic simulation loop in List. 5.1 just holds a reference to this interface without knowing the concrete implementation and how the agents' positions are updated. By applying this *strategy pattern*, different locomotion models can be included easily. Adding a new locomotion model requires implementing four methods:



(a) Time: 2.8 s　**(b)** Time: 6.8 s　**(c)** Time: 13.6 s

Figure 5.5: Agent positions at three different time steps using the optimal steps model

- `initialize()`: is called before the simulation starts, to initialize the locomotion model.
- `preLoop()`: is called before the simulation starts to carry out model-specific actions.
- `postLoop()`: is called after the simulation finished to perform clean-up actions.
- `update()`: is called in each simulation step to update the agents' positions.

Vadere's input and output Vadere stores all input parameters for the simulation, e. g. sources, targets and obstacles, in a JSON-based text file, see List. 5.2. The simulation output is written to a CSV-file, see List. 5.3. The output can be directly visualized in the Vadere GUI when the simulation is carried out and it can be replayed afterwards. Fig. 5.6 summarizes the typical steps to carry out a simulation in Vadere.

Listing 5.2: Vadere's JSON-based input file format. The input file stores all simulation parameters.

```
{
  "name" : "Sample Scenario",
  ...
  "scenario" : {
    "mainModel" : "...OptimalStepsModel",
    ...
    "attributesSimulation" : { },
    "topography" : {
      ...
      "obstacles" : [ ... ],
      "stairs" : [ ... ],
      "targets" : [ ...  ],
      "sources" : [ ... ],
      "dynamicElements" : [ ],
      "attributesPedestrian" : {
        "radius" : 0.195,
        "speedDistributionMean" : 1.34,
        "speedDistributionStandardDeviation" : 0.26,
        ...
      },
      ...
    }
  }
}
```

Listing 5.3: Vadere's CSV-based output file format: the positions of three simulated agents.

```
timeStep  pedestrianId     x     y
       1             1  1.67  4.87
       1             2  1.59  3.03
       1             3  1.31  2.51
       2             1  2.40  5.14
       2             2  2.29  2.77
       2             3  1.76  1.73
     ...
```

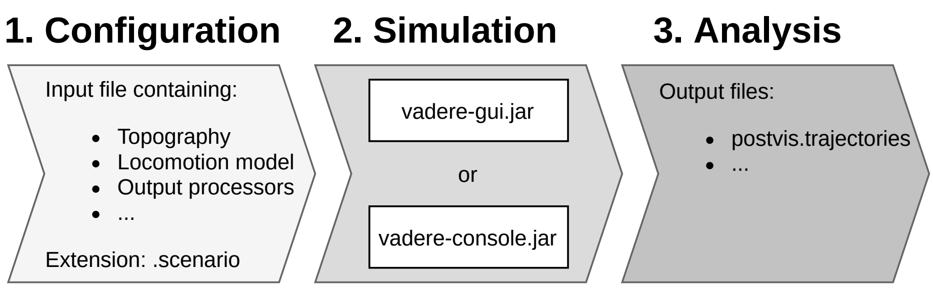


Figure 5.6: The three steps to carry out simulations with Vadere: **(1)** Configure the simulation parameters. **(2)** Use Vadere's graphical user interface or its command-line interface to run the scenario file. **(3)** Analyze the simulation output (mainly agent trajectories) by using the GUI or self-written scripts (e.g. in Python or Matlab) (own graphic but inspired by: Kleinmeier, Zönnchen, et al. 2019, p. 17).

5.3 Code quality measures

In this dissertation, I strive for a valid model of behavioral changes of agents which accurately replicates real-world observations. To ensure validity, I carry out simulations and compare them with real data in Sec. 7. But, a simulation model can only yield "accurate" results if the model is correctly implemented. To mitigate the probability of errors in the implementation phase, I apply the following measures:

1. I follow the clean code guidelines in Martin 2008. Especially, I use descriptive names for variables and methods instead of short and cryptic names. This ensures that my code can be understood and verified by non-experts. Descriptive names also avoid "magic numbers". For instance, see the variable `requiredFootSteps` in List. 2 (line 34, appendix 2, p. 169).

2. I program short methods, which solve a single problem at a time, in a test-driven approach. As first step, I implement the unit tests and then I code the actual method implementation. This leads to reusable methods with a well-defined interface. For instance, compare method `pedestrianCannotMove()` in List. 2 (line 30–42, appendix 2, p. 169).

3. I apply the continuous integration (CI) and continuous deployment (CD) practice (Beck 1999; Fowler 2006; Duvall, Matyas, and Glover 2007). That is, each committed source code change triggers a continuous integration pipeline. In the pipeline, first, verification tests are carried out (the unit tests). Then, basic validation tests are carried out. Several of them have been standardized by the research community (see RiMEA test cases, Sec. 2.5.1, p. 55). As last step, the Vadere simulator including my new model is packaged as ZIP package and is deployed to http://www.vadere.org/download/.

   The continuous integration/deployment approach brings two important benefits. On the one hand, continuous integration provides immediate feedback to developers and reveals if newly introduced code breaks existing functionality. On the other hand, continuous deployment makes Vadere and my new model easily accessible for users. Users just have to download the ZIP package and install the Java runtime environment as only dependency. Then, they can execute the simulator, try out my model and can report misbehavior. This continuous deployment approach promotes the scientific exchange between researchers and users. Fig. 5.7 visualizes the continuous integration/deployment pipeline which is implemented by using the Git version control system (Git Contributors 2015) and the GitLab repository manager (GitLab Contributors 2018).

4. I document code sufficiently so that other developers can use the code.

5. The code is open source and accessible for everyone under https://gitlab.lrz.de/vadere/vadere.

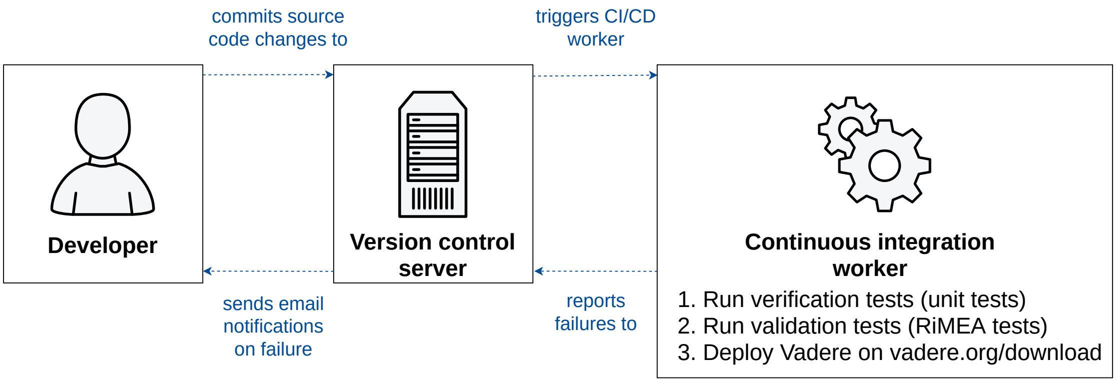


Figure 5.7: My continuous integration/deployment approach to promote scientific exchange with users. Changes to the source code trigger a continuous integration pipeline in which verification and validation tests are carried out (unit tests and RiMEA test cases) and finally the Vadere simulator is deployed to `http://www.vadere.org/download/`.

5.4 Summary

My model for behavioral changes of agents shall fulfill seven requirements: five functional and two non-functional requirements. One of my primary goals is described by the third functional requirement **F3:** the model architecture should fit for several simulators. This is utterly important because, currently, there are a plethora of simulators and simulation frameworks for pedestrian dynamics. My model should be beneficial for all of them and the whole pedestrian dynamics research community.

I will base my implementation on an established open-source simulator. This lowers the development effort because the locomotion layer must not be re-implemented. Additionally, an established simulator improves the sustainability of my model. An existing user base can directly apply my new model without getting familiar with a new simulation tool. I choose Vadere which is packaged with different locomotion models and a graphical user interface which makes the simulator easy to use.

I strive for a valid model which is error-free from an implementation point of view as much as this can be achieved. Thus, I will apply several measures to verify the correctness of my implementation. I will strongly follow the clean code guidelines by Martin 2008 and develop the code in a test-driven approach. A carefully configured continuous integration pipeline ensures that unit tests and validation tests are executed upon each source code commit.

Chapter 6

Modeling collective behavioral changes using a single concept: Implementation of a psychology layer

As worked out in the literature overview in Part I, there are two crucial aspects which lead to behavioral changes of humans: perception and cognition. Humans perceive their environment, process this (and additional) information and react accordingly by choosing from a repertoire of different behaviors. Fig. 6.1, p. 89, visualizes the most important modeling influences from the psychology of decision-making, from social psychology and locomotion modeling, and my operationalization of behavioral changes for pedestrian simulations.

As a first step, I will implement this observations as minimally-invasive and reusable architecture in the open-source simulator Vadere. This implementation follows an universal approach and can be reused in other pedestrian dynamics simulation tools. It is described in this chapter Sec. 6. In a further step, in Sec. 7, I will use real-world examples to enrich this generic architecture with application-specific knowledge from social psychology to make simulations more realistic and get behavioral changes of agents as emergent effect.

6.1 Operationalization of psychological processes to a reusable model[1]

Like for any other simulation software, a pedestrian stream simulator's core is a simulation loop in which time is incremented. In this loop, a locomotion model is responsible for finding the next position for each agent in each simulated time step (compare List. 6.1).

[1] The content of the following two sections follows and enlarges on my peer-reviewed publication Kleinmeier, Köster, and Drury 2020, p. 7–9. The two sections reflect my own and personal modeling efforts to allow behavioral changes of agents.

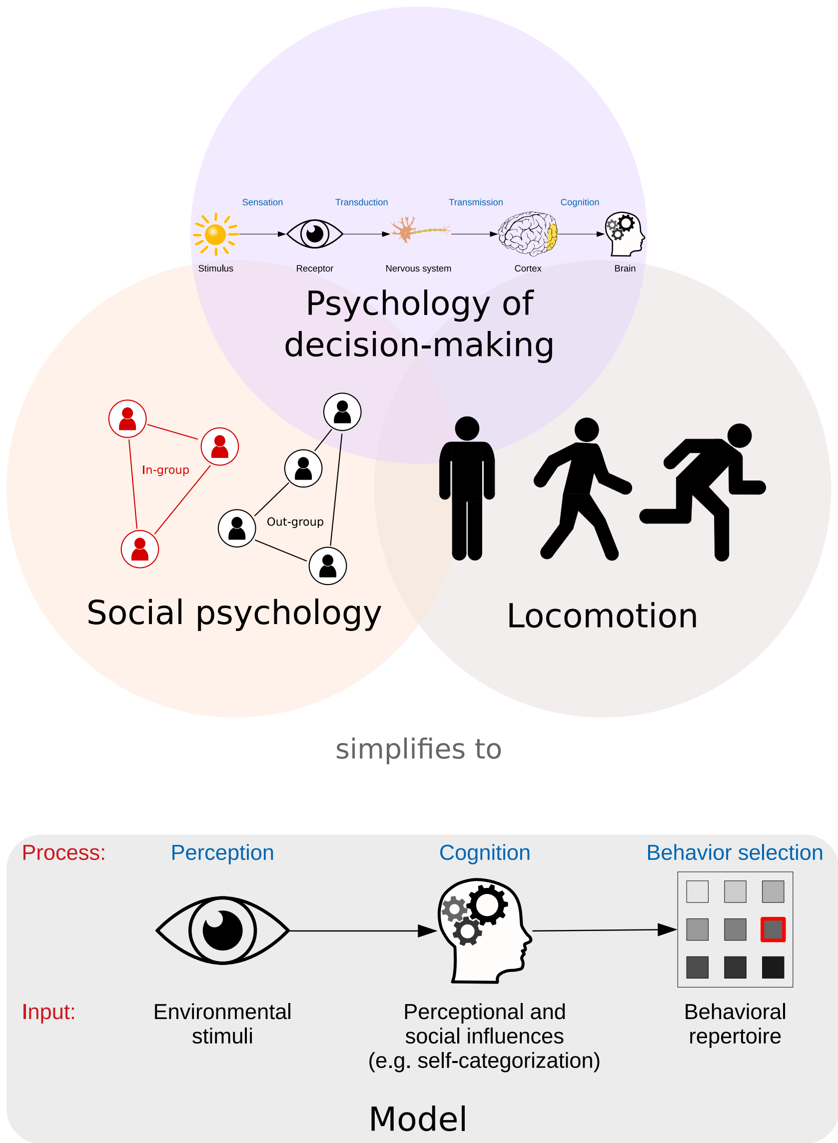


Figure 6.1: From the real-world complexities to a simplified and reusable model to allow behavioral changes of agents: real human perceive their environment, process this (and additional) information and react accordingly by choosing from a repertoire of different behaviors.

Listing 6.1: A typical simulation loop of a pedestrian stream simulator (listing: Kleinmeier, Köster, and Drury 2020, p. 7).

```
while (simulationIsRunning) {
  ...
  // A locomotion model searches the next
  // position for an agent which is closer
  // to a target than currently.
  locomotionModel.update(agents, time);
  ...
  time++;
}
```

Most of the current locomotion models (Helbing and Molnár 1995; Antonini, Bierlaire, and Weber 2006; Seitz and Köster 2012; Dietrich and Köster 2014) only include physical aspects to navigate an agent through an environment. For instance, obstacles repel an agent while targets attract agents.

But, the key is to include also the psychological status of an agent in each simulation step. This layer represents the mental processes of perception and cognition of real humans (Gerrig 2013, p. 206 ff.) and effects the behavior of an agent. Additionally that means, instead of having just one behavior — that is, moving towards a target — an agent must have a behavioral repertoire from which the agent can choose to react to its environment. For pedestrian stream simulations that means, that agents

- on perception sub-layer, perceive environmental stimuli in a sight / search radius r.
- on cognition sub-layer, use information from the perception sub-layer and enrich it with information about neighboring agents to include the social psychology perspective. Agents can categorize themselves as in- or out-group members in comparison to their neighboring agents and follow the social norms of this group. For instance, in-group members trust each other and imitate behavior of other in-group members to allow collective actions across agents. I employ the term self-category here because the social psychologists Templeton and Neville state that "self-categorisation [...] becomes the psychological basis for crowd behavior" (Templeton and Neville 2020b, p. 20).
- on locomotion layer, agents choose from a repertoire of different behaviors (e. g., wait, make step towards target, swap with other agent) to get closer to their physical target.

Fig. 6.2, p. 91, visualizes the sequential processing of information inside the introduced psychology layer. The lower layers, e.g. `Cognition`, only process the information from the direct upper layer. That means, an agent firstly perceives environmental stimuli, then an agent processes this information in the cognition layer and enriches it with further information. This simple architecture reflects what real humans do: they perceive, process and react to this information with a specific behavior. For instance, look up the figures in Sec. 7 to see the model in action and how target-oriented agents become cooperative and swap places to reach their targets.

The main advantage of those clearly separated psychology layers is that experts in psychology or other fields can implement the perception and cognition sub-layer without knowing implementation details of the pedestrian stream simulator. A locomotion expert can implement specific locomotion strategies. For instance in a scenario with counterflowing agents, if cooperative behavior does not mean swapping two agents, another locomotion strategy can be implemented on the locomotion layer. This clean software architecture makes it possible to work on a pedestrian stream simulator interdisciplinarily combining knowledge from different research domains, like proposed by Templeton and Neville 2020b, p. 46.

Introducing this psychology layer (with sub-layers perception, cognition and pre-existing locomotion) modifies the existing simulation loop List. 6.1 only very slightly and keeps the overall software architecture simple and easy to implement according to the KISS principle (Axelrod 1997, p. 18 Martin 2008, p. 10), compare List. 6.2.

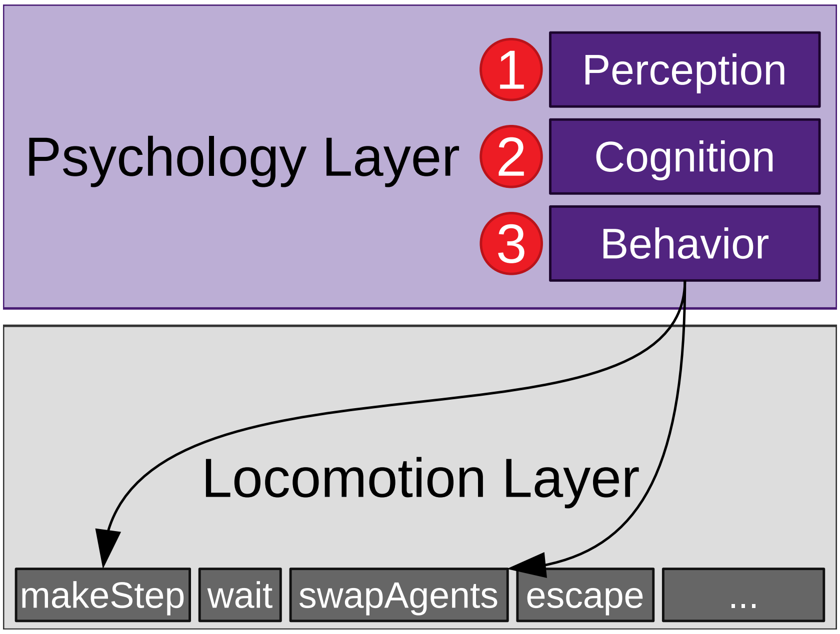


Figure 6.2: The three sequential phases of the new psychology layer: firstly, agents perceive environmental stimuli. Secondly, agents process these information in a cognition phase and enrich it with further (context-relevant) information. Thirdly, agents react to the processed information by selecting a behavior from a behavioral repertoire on locomotion layer. The behavioral repertoire on the locomotion layer should cover different real-world situations. For instance, make a step towards a target (e. g., a train station), wait at a platform (that is, to not move) or escape when a stimulus is perceived as threat (which consists of several locomotion patterns) (own graphic but inspired by: Kleinmeier, Köster, and Drury 2020, p. 7).

Listing 6.2: The new simulation loop which contains the added psychology layer with sub-layers perception, cognition and behavior (listing: Kleinmeier, Köster, and Drury 2020, p. 8).

```
while (simulationIsRunning) {
  ...
  // Perception
  perceptionModel.update(agents, stimuli);
  ...
  // Cognition
  cognitionModel.update(agents);
  ...
  // Locomotion
  locomotionModel.update(agents, time);
   |
   +-> if (agent.selfCategory == COOPERATIVE) {
         Agent candidate = findSwapCandidate();
         swapAgents(agent, candidate);
       }
  ...
  time++;
}
```

`perceptionModel` and `cognitionModel` are implementations of interfaces. Using this design decision — the strategy pattern — allows to extend a pedestrian stream simulator to a tool to also test psychological hypotheses. That means that it is possible to change the perception and cognition model for each simulation run and to cover different real-world situations. For instance, a protest march differs from a daily commuting situation which affects humans' perception, cognition and locomotion, e. g. the personal space. The personal space is a small protective sphere that humans maintain between themselves and others (Hall 1966, p. 119). For instance, humans allow closer proximity to others in an overcrowded subway but keep a greater distance from each other in an open space. Using an interchangeable approach also reflects the fact that a simulation tool cannot provide a "one-fits-all-situations" model. Therefore, I facilitate interfaces with only two methods here, see UML diagrams Fig. 6.3 and Fig. 6.4

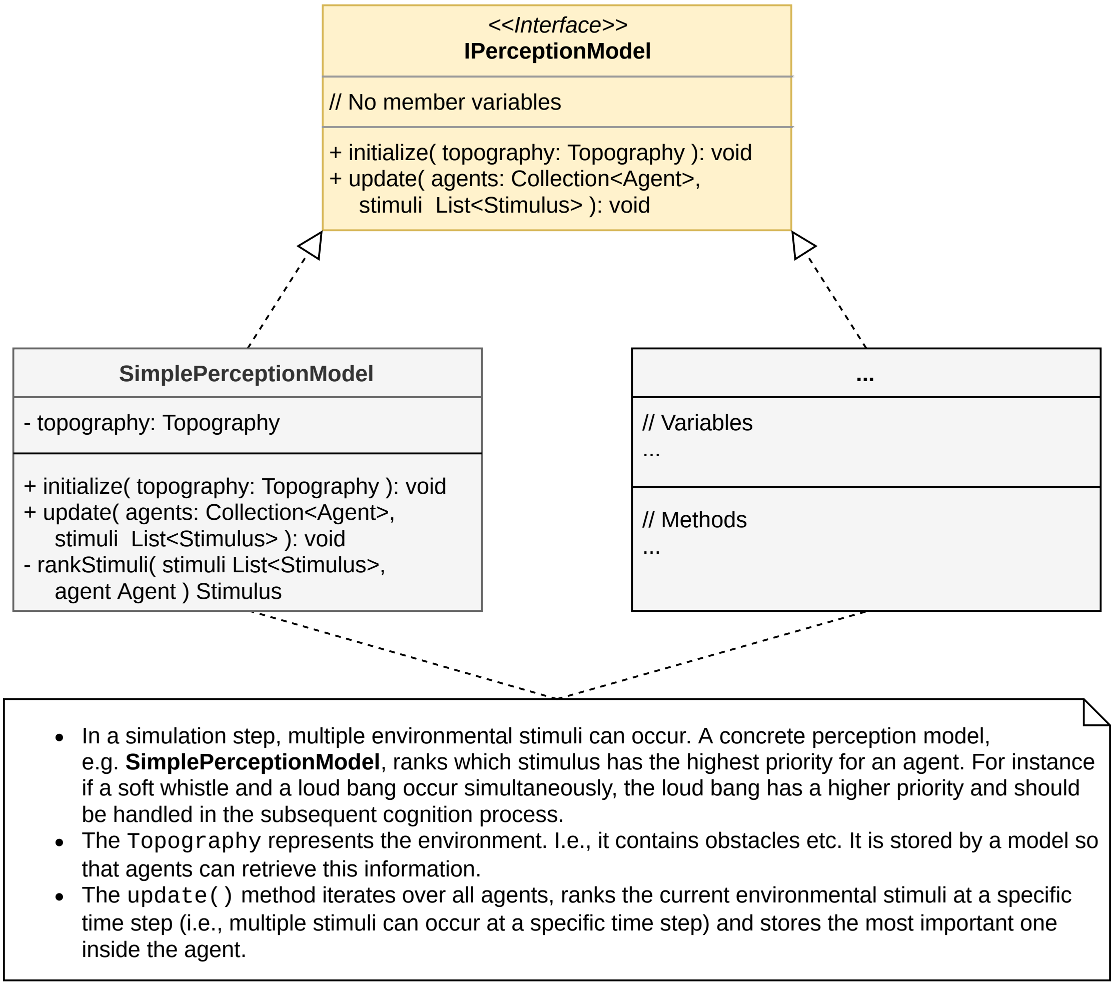


Figure 6.3: UML diagram of the interface and interface implementations of the perception sub-layer. Private access is prefixed with the minus symbol and public access is prefixed with the plus symbol.

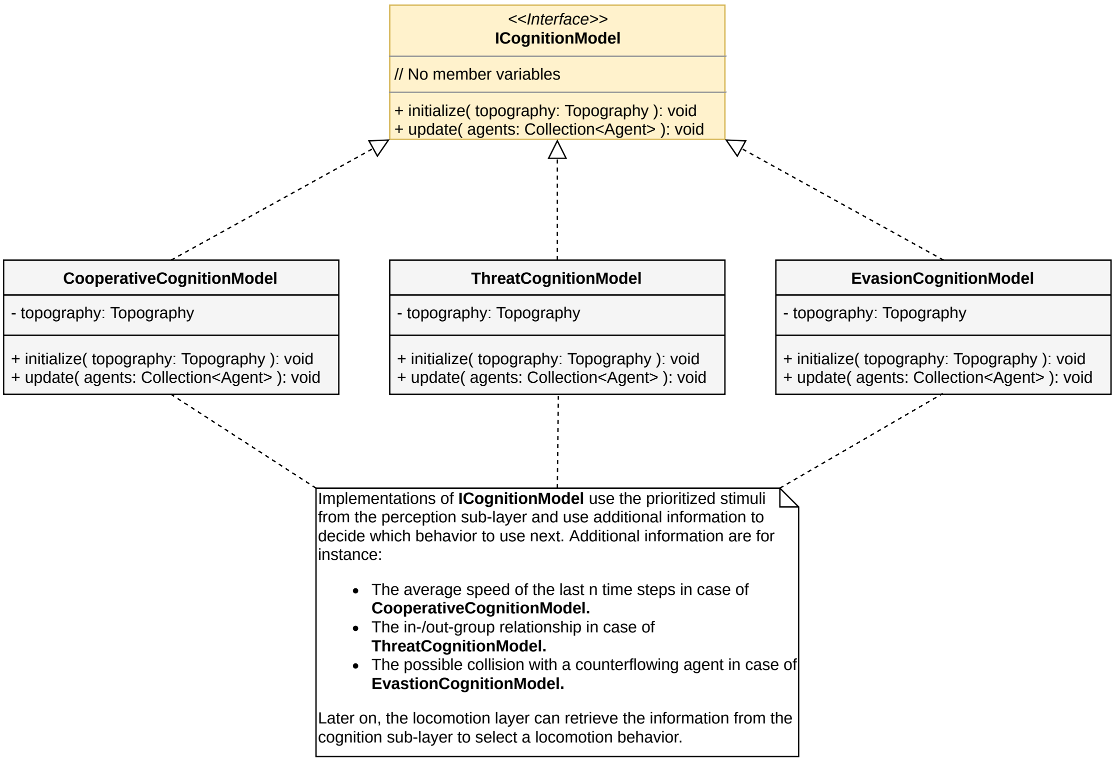


Figure 6.4: UML diagram of the interface and interface implementations of the cognition sub-layer. Private access is prefixed with the minus symbol and public access is prefixed with the plus symbol.

The final psychological status, after processing the perception and cognition sub-layer, is stored inside the agent and can be retrieved on the locomotion layer to select the appropriate action, compare Fig. 6.5, p. 94. Such a detailed psychology status reflects latest ideas from social psychologists to enhance pedestrian simulations. Templeton and Neville formulated following requirements for new agent-based crowd models (Templeton and Neville 2020b, p. 47 ff.):

- “First, each agent should be given the ability to have both a personal and social identity.”
  This is reflected in my new model by the broader concept of (social) categories which can cover different real-world scenarios. I argue that category names like `TARGET_ORIENTED` or `COOPERATIVE` are easier to interpret in terms of locomotion behavior than (social) identities like “father” or “football supporter”.

- “Second, agents should be given social identities and the ability to know both their own social identity and the social identities of others.”
  The self-category is stored in each agent and can be retrieved by other agents in each simulation loop.

- “Third, further research could focus on the changing perceptions of group membership and the implications this has for levels of help provided among crowd members.”

Additionally to the self-category, in my model, an agent also stores its group membership in terms of in- and out-group membership. Two (or more) in-group members trust each other and can collaboratively act together by imitating behavior (that is, changing the self-category). Contrarily to in-group members, out-group members do not trust each other and stick to their social category in the course of a simulation.

Adding a self-category and a group membership to each agent is a simple implementation of Turner's self-categorization theory. This allows agents to identify their own social category and also others' category in the course of a simulation and to change the category as consequence of environmental stimuli or social events. Additionally, the group membership allows to identify other agents as in- or out-group members and allows collective actions among in-group members which was reported by several social psychologists in the past (Reicher 1984; Drury, Cocking, and Reicher 2009a; Drury, Cocking, and Reicher 2009b).

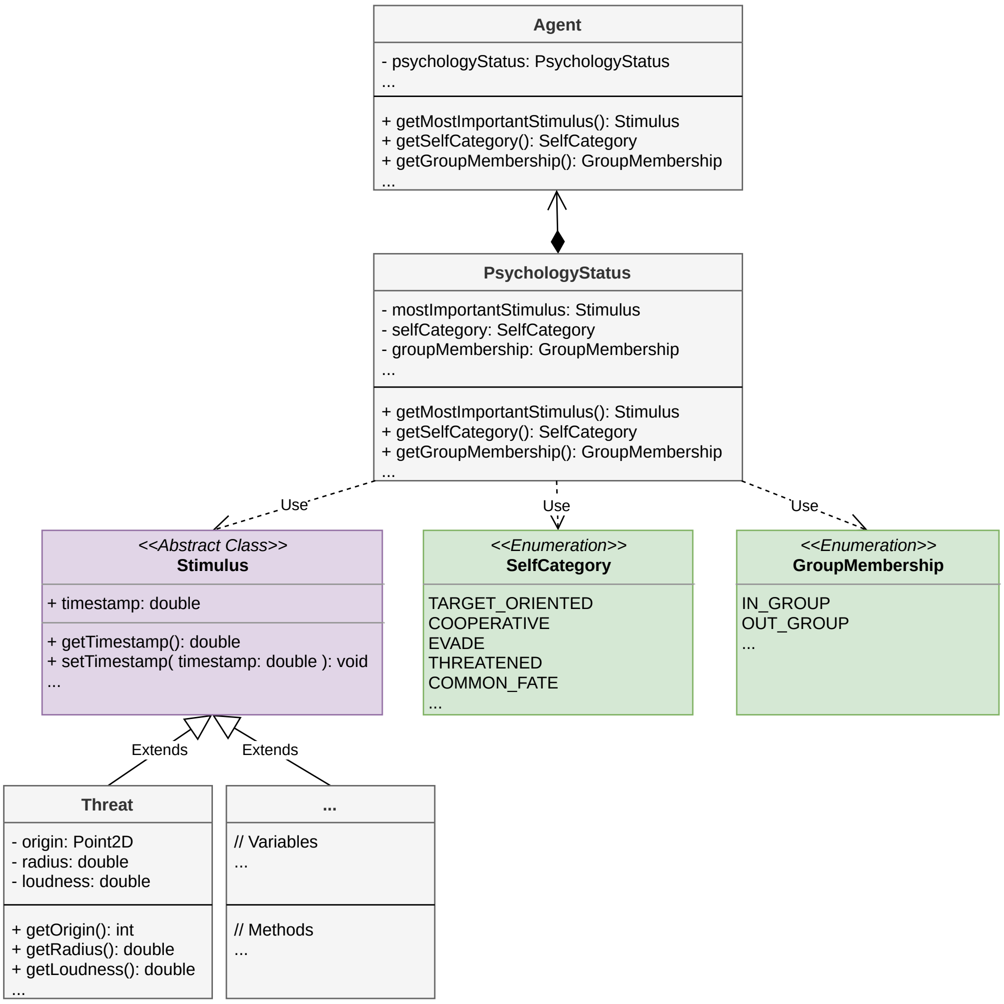


Figure 6.5: The psychology status is stored in the agent class. It consists of the currently most important stimulus, the agent's self-category and agent's group membership in terms of in- and out-groups.

As Fig. 6.5 shows, I introduce the following categories in the enum `SelfCategory` as first step towards the self-categorization theory: `TARGET_ORIENTED`, `COOPERATIVE`, `EVADE`, `THREATENED` and `COMMON_FATE`. These first categories are required to accurately reenact the real-world use cases in Sec. 7. One could argue that these are not typical categories as used in social psychology, because psychologists demand (social) identities as result of a self-categorization process. Instead, these categories indicate which behavior is expected on the locomotion level as a result of the self-categorization. I argue as follows:

1. `TARGET_ORIENTED`: Being target-oriented is the behavior of a person whose salient social identity makes to look at the people around him/her as out-group. Such target-oriented persons act more competitive by blocking others and they try to leave a scene as quickly possible without helping others.

2. `COOPERATIVE`: In contrast, cooperative persons categorize themselves as in-group members and help each other. In a dense crowd, a cooperative person would swap places with another cooperative person. In-group members are willing to imitate or copy behavior of other in-group members because they trust each other.

3. `EVADE`: Evading others is a consequence of a person's categorization as out-group to others. In contrast to the target-oriented category, others are seen more friendly and they are not blocked or hindered as target-oriented identities would do.

4. `THREATENED`: Persons categorize themselves as threatened as an immediate response to dangers or hazards. As an immediate reaction, people's goal is to flee and others are recognized as out-group and are ignored.

5. `COMMON_FATE`: Besides feeling out-group to each other as immediate reaction to a threat, it was also reported that people share a common fate identity a bit after a threat was perceived. For example, after the bombings in the London subway in 2005, survivors of the bombings helped each other instead of fleeing egoistically (Drury, Cocking, and Reicher 2009b). The survivors shared a common fate after being inside the same threat area.

I argue that all five introduced categories are a result of a self-categorization process. This categorization process and the change between the categories can lead to different collective behaviors as we will see in the use cases in Sec. 7. For the sake of simplicity and making the architecture reusable, I directly map the result of the cognitive process to a (social) category which better describes what is expected on locomotion layer instead of introducing identities. Otherwise, another layer of complexity would have to be added with social identities (e. g. commuters) and different norms and behaviors for each identity (e. g. target-oriented, cooperative etc.). My proposed categories must be seen as a starting point for more elaborated social categories.

6.2 Implementation steps

The operationalized psychology layer from Sec. 6.1 is implemented in `Vadere` (Kleinmeier, Zönnchen, et al. 2019; Vadere team 2020). The following steps are carried out:

1. Add the psychological state to agents by introducing model classes (compare UML diagram in Fig. 6.5, p. 94):
   a) Add abstract class `Stimulus` and concrete stimuli implementations like `Threat` (with an origin, a loudness and a radius).
   b) Add enums `SelfCategory` and `GroupMembership`.
   c) Add class `PsychologyStatus`, as wrapper for `Stimulus`, `SelfCategory` and `GroupMembership`, to `Agent` which allows to update the psychological state in each simulation step.
2. Update the psychological state in each simulation step by introducing controller classes for perception and cognition:
   a) Add interfaces `IPerceptionModel` and `ICognitionModel` (see UML diagrams Fig. 6.3, p. 92, and Fig. 6.4, p. 93).
   b) In a first step, implement simplified controllers for perception and cognition. Later on, replace simplistic implementations with application-specific knowledge from experts. As first step, implement `SimplePerceptionModel` and `SimpleCognitionModel`. `SimplePerceptionModel` just ranks the occurred stimuli (which is necessary if multiple stimuli occur simultaneously). For instance, a `Threat` has a higher priority than a red traffic light. `SimpleCognitionModel` fixes an agent's `SelfCategory` to `TARGET_ORIENTED` unless a high-priority stimulus is perceived, compare List. 6.3, p. 97.
3. Extend the behavioral repertoire of agents and use it on locomotion layer:
   a) Add class `OSMBehaviorController` to encapsulate different locomotion strategies for the optimal steps model.
   b) Implement methods like `makeStepToTarget()`, `wait()`, `swapPedestrians()` to cover a wide range of real-world scenarios.
   c) During `locomotionModel.update()`, evaluate `agent.getSelfCategory()` and react accordingly, compare List. 6.4, p. 97.

Listing 6.3: The `update()` method of class `SimpleCognitionModel`.

```java
public class SimpleCognitionModel implements ICognitionModel {
    ...
    public void update(Collection<Pedestrian> pedestrians) {
        for (Pedestrian pedestrian : pedestrians) {

            Stimulus stimulus = pedestrian.getMostImportantStimulus();
            SelfCategory nextSelfCategory;

            if (stimulus instanceof Threat) {
                nextSelfCategory = SelfCategory.THREATENED;
            } else if (stimulus instanceof ElapsedTime) {
                nextSelfCategory = SelfCategory.TARGET_ORIENTED;
            } else {
                throw new IllegalArgumentException(...);
            }

            pedestrian.setSelfCategory(nextSelfCategory);
        }
    }

}
```

Listing 6.4: The `update()` method of class `UpdateSchemeEventDriven` of the optimal steps locomotion model.

```java
public class UpdateSchemeEventDriven implements UpdateSchemeOSM {
...
    void update(PedestrianOSM pedestrian, double timeStepInSec, double
    currentTimeInSec) {
        ...
        SelfCategory selfCategory = pedestrian.getSelfCategory();

        if (selfCategory == SelfCategory.TARGET_ORIENTED) {
            osmBehaviorController.makeStepToTarget(pedestrian, topography
    );
        } else if (selfCategory == SelfCategory.COOPERATIVE) {
            PedestrianOSM candidate = osmBehaviorController.
    findSwapCandidate(pedestrian, topography);

            if (candidate != null) {
                pedestrianEventsQueue.remove(candidate);
                osmBehaviorController.swapPedestrians(pedestrian,
    candidate, topography);
                pedestrianEventsQueue.add(candidate);
            } else {
                osmBehaviorController.makeStepToTarget(pedestrian,
    topography);
            }
        }
        ...
    }
}
```

6.3 Making the psychology layer optional

In an additional step, I recommend to make the new psychology layer optional. This has two benefits: **(1)** It saves computational time in each simulation step when no psychological aspects are required to reenact a real-world observation. **(2)** It retains the original simulator purpose (mostly evacuations) and agents do not change their behavior. That is, in most simulators, agents act in a target-oriented way and agents shall move closer to their targets in each simulation step. Making the psychology layer optional requires to introduce a boolean flag `usePsychologyLayer` in the simulation loop. If this flag is `false`, the perceptional and cognitive phases are skipped and only the locomotion layer is executed in each simulation step.

Listing 6.5: Making the psychology layer optional saves computational time and keeps the original simulator behavior. It only requires to introduce a boolean flag `usePsychologyLayer`.

```
scenarioFile = readScenarioFile(filename);

while (simulationIsRunning) {
  ...
  if (scenarioFile.usePsychologyLayer()) {
    perceptionModel.update(agents, stimuli);
    cognitionModel.update(agents);
  }

  locomotionModel.update(agents, time);
  time++;
}
```

6.4 Summary

In the literature overview in Part I, I presented a wide range of factors which influence the human decision-making process and lead to changes in human behavior. My goal is to establish a reusable software architecture which can be also applied to different pedestrian stream simulators as a benefit for the whole pedestrian dynamics research community. Therefore, I chose a minimally invasive implementation. I focused on the three crucial psychological aspects perception, cognition and a behavioral repertoire. These three aspects are realized as three sequential steps in the simulation loop of Vadere. First, an agent perceives environmental stimuli. Then, an agent uses this information and adds additional information (like the `SelfCategory` of neighboring agents) to process this information in a cognitive process. Lastly, based on this cognitive process, the agent uses its `SelfCategory` to select a locomotion action from the behavioral repertoire. To this end, I added a `PsychologyStatus` to agents which is updated in each simulation step.

This approach is a straight-forward mapping of psychological processes (perception and cognition) to a clean and re-usable software architecture. I applied the strategy software design pattern on the perception and cognition phase. That is, the simulation loop of Vadere only knows the interfaces `IPerceptionModel` and `ICognitionModel`. Perception and cognition experts can provide different implementations for these interfaces to cover a wide range of real-world examples. Then, simulator users can employ different perception and cognition models for each simulation run. This clear separation allows experts in corresponding fields to implement their findings without knowing the rest of the simulation framework. This requires minimal programming experience and allows working interdisciplinarily on a pedestrian stream simulator and combining expertise from natural and life sciences. Despite the minimal changes in the software architecture, this implementation fundamentally improves on Vadere. It now is not only a tool to test locomotion hypotheses, but also a tool to explore psychological hypotheses about perception and cognition. The architecture is minimally invasive and can easily be implemented in other simulators.

Of course, this approach is a simplification of the real world. For instance, the perception process does not cover all the sensory aspects like transduction or transmitting neural impulses. But, I argue that this simplification is necessary to obtain a reusable architecture for pedestrian simulators which can be easily understood by a wide range of researchers: from sociologists and psychologists to mathematicians and computer scientists. Also, not all intricacies of the perception process need to be covered to obtain a correct model of behavioral changes.

Chapter 7 Model validation and application: Demonstrating behavioral changes of agents in simulations towards natural behavior

As the British mathematician George Box said, “all models are wrong, but some are useful” (Box 1976). That’s certainly true because scientific models always fall short of the complexities of reality. Nevertheless, with my work I strive for a model that is useful for other researchers and practitioners like crowd managers. Especially, practitioners can benefit from simulations by trying out “what if” scenarios in the planning phase of crowd events to avoid casualties like seen in the past (e. g., at the Love Parade music festival 2010 in Germany, see Helbing and Mukerji 2012). Simulations can help to detect critical high densities or to test how environmental stimuli like a loud bang can change the atmosphere at an urban parade from a peaceful march to a chaotic escape situation. To ensure the usefulness of my new model for behavioral changes of agents presented in 6, I base my validation on three pillars:

1. I implement approved psychological theories which are carefully identified by the thorough literature review in Sec. 3 and Sec. 4.
    - These theories are accepted by the psychological community and were reviewed by experts in this field.
    - Additionally, these theories have been applied in practice for several years and have shown their usefulness.
2. I test the model implementation quantitatively and qualitatively against empirical data.
    - The quantitative and qualitative data is derived from an own experiment which I conducted at the Munich University of Applied Sciences with 58 participants in October 2018.
    - More qualitative data is derived from a real-world incident at Oxford Street, London, in 2017 were a false alarm caused thousands of people to change their behavior from shopping to escaping.

3. I carry out a sensitivity study to reveal the effects of introduced parameters.
   - The overall goal is to keep the number of introduced parameters small to make the model understandable by different research communities, both natural and life sciences.
   - I vary input parameters systematically and test the effect on interesting output quantities.

Concretely, I will demonstrate the versatility of my modeling approach from Sec. 6.2 by using two real-world use cases and one fictional use case. Before carrying out simulations, I will use the generic architecture from Sec. 6.2 to add application-specific knowledge to the cognition layer to be able to reenact the observed behavior from the use cases. The following three use cases will be shown:

- The first use case represents an own experiment and is validated quantitatively and qualitatively.
- The second use case represents a false-alarm which occurred at Oxford Street in 2017. This use case is validated qualitatively and effects of introduced model parameters are tested in a sensitivity study.
- The last use case, a fictional scenario with counterflowing agents in a narrow corridor, is validated qualitatively.

In the following, I describe the scenario, the application-specific knowledge complementing the generic architecture from Sec. 6.2 and the simulation results for each use case in more detail.

My goal for all simulations is to use default parameters of existing code which I used as foundation. Especially, this holds for locomotion parameters as they were defined by the original authors, for instance, the default parameters of the optimal steps model as defined in Seitz 2016. My implementation shall seamlessly work with an existing simulator to show that this approach can be used in other simulators as well without heavily tweaking of existing code.

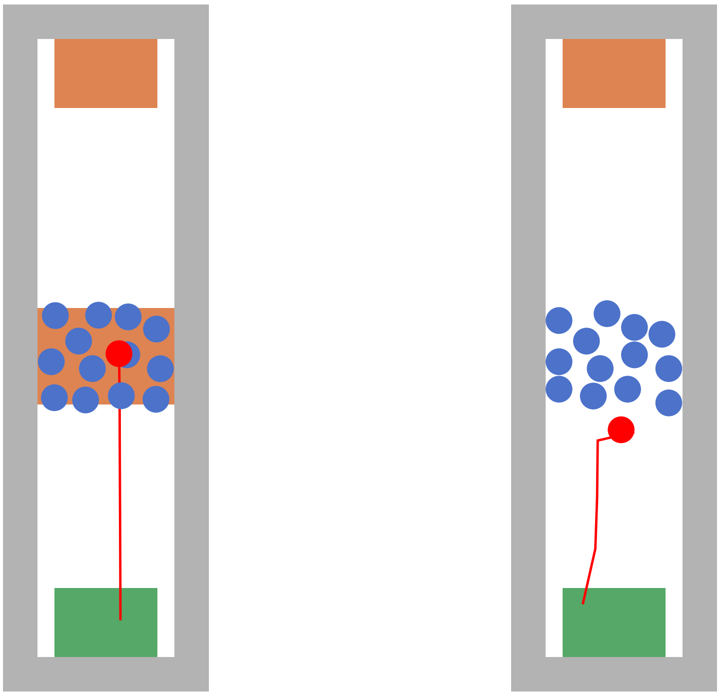
7.1 Use case 1 — Experiment: Motion through a dense and stationary crowd (at Munich University of Applied Sciences 2018)[1]

This use case represents an own experiment which I conducted at the Munich University of Applied Sciences in 2018 and is validated quantitatively and qualitatively.

[1]The content of this section follows and enlarges on my peer-reviewed publication Kleinmeier, Köster, and Drury 2020. The content reflects my own and personal contribution to the experiment, the experiment analysis and the derived model for cooperative behavior. The publication was supported by well-respected co-authors from mathematical modeling and social psychology. To ensure consistency in this work, I mostly chose the “I” formulation in this section even if my arguments were backed up by the co-authors.

7.1.1 Scenario description

Simulations for pedestrian dynamics are nowadays used to make crowd gatherings safer. Yet, the underlying pedestrian stream models only work well for very specific scenarios. For instance, unidirectional pedestrian flows or queuing behavior. But often locomotion models fail for setups that seem only slightly different. For instance, when a first aid-attendant needs to forge a path through a dense crowd to reach an injured person. When reenacting such a real-world situation in current simulation tools, agents often get stuck and end up in a deadlock situation. This is because there is no real interaction between agents, compare Fig. 7.1.



(a) Social force model

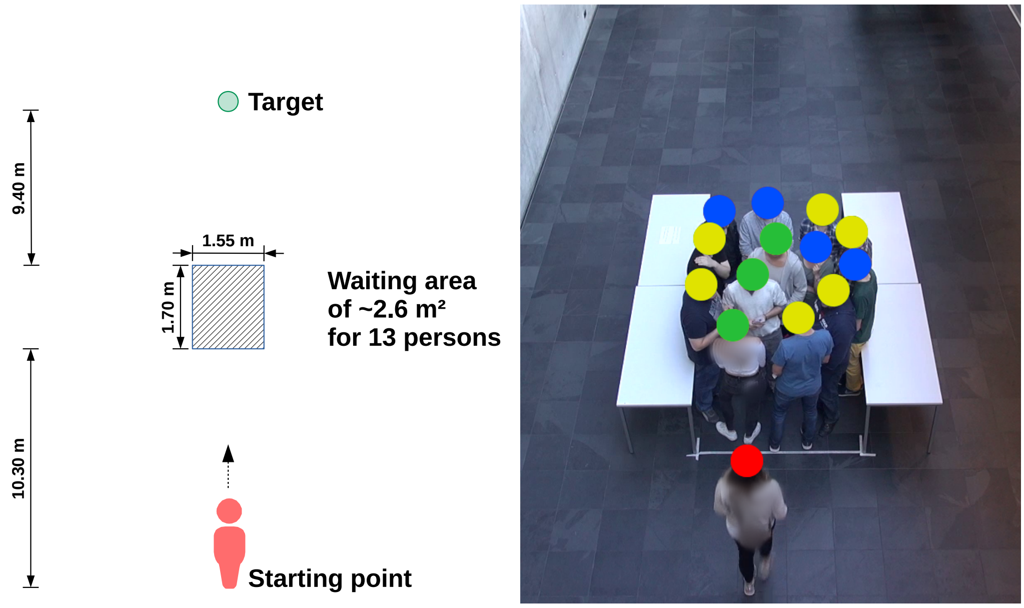
(b) Optimal steps model

Figure 7.1: A walking agent (red) starts walking at the bottom area and tries to reach the rectangular target area on top while confronted with a dense, stationary crowd. In simulations, one cannot observe real interaction between agents when using different physically-inspired locomotion models. Either the walking agent "ignores" the dense, stationary crowd and walks on other agents which could not happen in real life **(a)**. Or the crowd blocks the walking agent completely because of the high density **(b)**. The open source simulator Vadere was used for the simulations (image: Kleinmeier, Köster, and Drury 2020, p. 2).

From real life, we know that humans interact with each other and act cooperatively. Imagine a crowded music festival where participants forge their path to the toilette. But, today's pedestrian models mostly focus on locomotion aspects solely and neglect the psychological aspects which influence human decision-making to resolve the aforementioned scene at the music festival. In order to reveal how humans interact cooperatively with each other in a high-density situation, I conducted a controlled experiment in the foyer of the Munich University of Applied Sciences on Oct 12, 2018 (11:45 – 13:00). A controlled experiment allowed me to have the full control about the environment and to avoid priming of participants and observer biases (Gerrig 2013, p. 20–37). The whole experiment is described in more detail in Kleinmeier, Köster, and Drury 2020. The measures I took to avoid observer biases and priming are outlined in Kleinmeier and Köster 2020.

Experiment setup In the experiment, I observed how a participant walks through a dense, waiting crowd. To this end, I kept 58 participants in a separate waiting room. The participants were entertained by experiment assistants with quizzes and discussions to keep the atmosphere as normal as possible. To avoid any priming, the participants received minimal information. The participants signed an informed consent form with the title "Study on movements of pedestrians". The form stated that no physical risks were involved and that the experiment was recorded on camera. I chose first-year students in their second week as participants to ensure that they did not know anything about the experiment's intentions.

During the experiment, 13 participants stood in a delimited area of $2.64\,\mathrm{m}^2$ ($1.55\,\mathrm{m} \times 1.70\,\mathrm{m}$) as a waiting crowd. In each experiment run, the walking participant successfully crossed the crowd along what would be the y-axis in Fig. 7.2. The density while crossing was $\rho = 5.30\,\mathrm{ped/m}^2$. For each experiment run, I randomly chose one person from the waiting room and assigned this person as walking participant. For the very first run, I also chose 13 persons from the waiting room and assigned them as waiting crowd. The experiment set-up is depicted in Fig. 7.2 and described in more detail in Kleinmeier and Köster 2020.

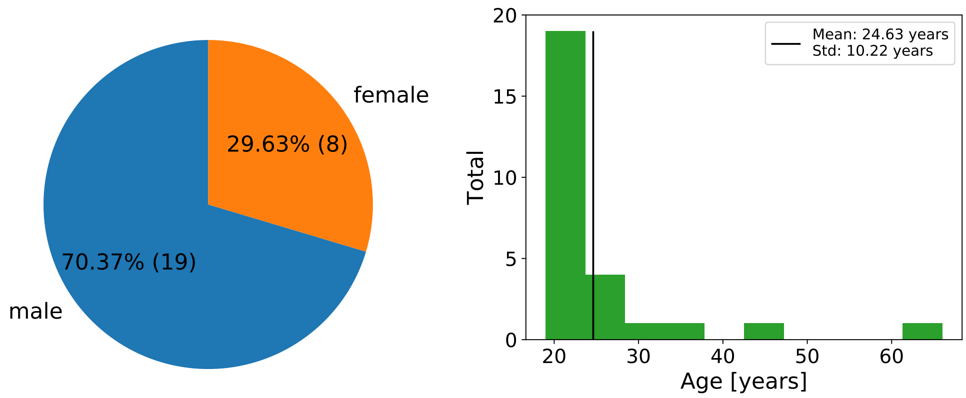


(a) Schematic experiment setup **(b)** Real experiment setup

Figure 7.2: The experiment setup: a waiting crowd of 13 participants in a delimited area of $2.64\,\mathrm{m}^2$ is successively crossed by a participant (image: Kleinmeier and Köster 2020, p. 3).

I took two measures to avoid training effects for the waiting crowd: **(1)** After each run, a staff member shuffled the waiting crowd. To this end, the waiting crowd were asked to leave and re-enter the waiting area, so that the positions of the participants were shuffled. **(2)** After five runs, seven random participants of the waiting crowd were replaced by seven participants from the waiting room, who were also chosen randomly. I also took several measures to avoid observer biases like using a standardized experiment procedure with consistent instructions for all participants. The walking participants were instructed with the sentence “Go to the tree by crossing the crowd”. The waiting crowd was instructed with “Wait in the delimited area”. See Kleinmeier and Köster 2020 for a description of all measures against observer biases. Tables on the left- and right-hand side of the waiting area prevented the participants from leaving the waiting area accidentally.

In total 58 students participated in the experiment. 27 of them (men and women), aged 19–66, were assigned as walking participants and performed 30 runs (compare Fig. 7.3). I collected gender, age, height and shoulder width for each walking participant.



(a) Gender **(b)** Age

Figure 7.3: Gender and age distribution of the 27 walking experiment participants (image: Kleinmeier, Köster, and Drury 2020, p. 4).

The experiment was filmed from above at an angle of around $60°$ (compare Fig. 7.2). I recorded the experiment with a camcorder, the Sony Handycam HDR-PJ780VE, using a resolution of $1280\,\mathrm{pixel} \times 720\,\mathrm{pixel}$ and $25\,\mathrm{frames\ per\ second}$. The raw video material had a length of $73\,\mathrm{minutes}$. I used the free video analysis and modeling tool `Tracker` (Tracker Contributors 2019) to correct the optical distortion and to track the trajectories of the walking participant and the waiting crowd. I used self-written Python scripts, more precisely Jupyter notebooks, to analyze the data.

Experiment results Together with final-year students I carefully analyzed the video material in course of the “modeling seminar” lecture at the Munich University of Applied Sciences during the winter term 2018/2019. After watching the video footage, we formulated hypotheses of the observed behavior and measured the effect size of the behavior. The video analysis yielded three hypotheses:

- Pedestrians walking through a crowd are slowed down.
- The pedestrians in a waiting crowd return to their initial positions after giving way to the “intruder”.
- Real humans can pass a crowd at high densities.

The last hypothesis, while seemingly trivial, is crucial because this is where current simulations fail but my new psychology layer from Sec. 6 will help to address this shortcoming as we will see in this section.

Speed measurements of walking participants Fig. 7.4 and Tab. 7.1 provide an overview of the averaged instantaneous speeds of all walking participants.

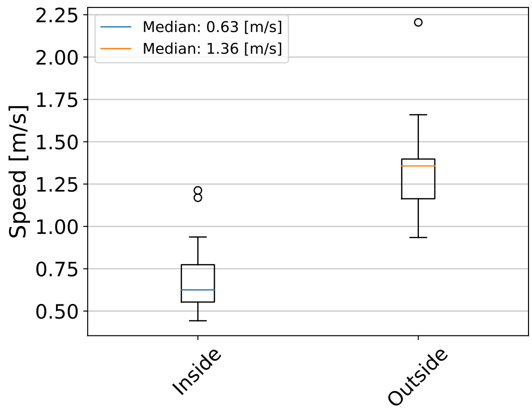


Figure 7.4: Box plot for speed distribution (averaged instantaneous speeds) of the walking participants inside and outside the waiting crowd (image: Kleinmeier, Köster, and Drury 2020, p. 4).

	Speed [m/s] **inside**	**outside**
sample size	30.00	30.00
mean	0.70	1.33
std	0.19	0.25
min	0.44	0.93
25%	0.55	1.16
50%	0.63	1.36
75%	0.77	1.40
max	1.21	2.20

Table 7.1: Detailed statistics for the measured speed distributions of the walking participants inside and outside the waiting crowd (table: Kleinmeier, Köster, and Drury 2020, p. 4).

Comparing the mean instantaneous speed of $0.70\,\mathrm{m/s}$ (inside) and $1.33\,\mathrm{m/s}$ (outside) supports the hypothesis that the walking participants are slowed down by the waiting crowd. The detailed analysis can be found in Kleinmeier, Köster, and Drury 2020 along with a statistical significance test for the speed measurements.

Distributions of waiting crowd A second measurement revealed that the crowd members tend to return to their initial positions before the walking participant entered the crowd. I used two metrics to draw this conclusion. Firstly, I measured the Euclidean distance between the initial position — before the walking participant entered the waiting crowd — and the end position of each crowd member. Then, I measured the maximum Euclidean distance a participant of the waiting crowd moved while the crowd was crossed by the walking participant. Both measurements are visualized in Fig. 7.5 and Fig. 7.6, accompanied by Tab. 7.2 and Tab. 7.3.

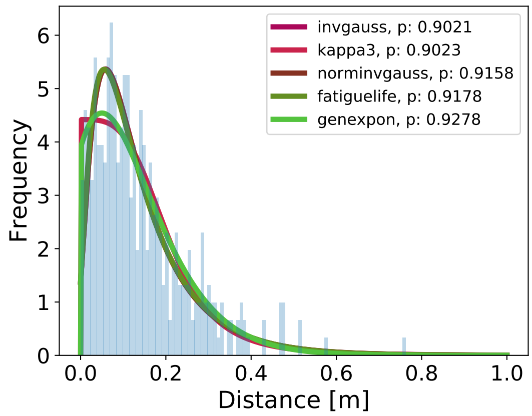


Figure 7.5: The data in blue visualizes the Euclidean distances between a participant's initial position — before the walking participant entered the waiting crowd — and the end position. The Euclidean distance is defined as $||p_{initial} - p_{end}||_2$ with $p \in \mathbb{R}^2$. The plot includes the best-fitting continuous distributions with a p-value ≥ 0.90 (image: Kleinmeier, Köster, and Drury 2020, p. 5).

	Distances [m] **(metric 1)**
sample size	400.00
mean	0.14
std	0.11
min	0.00
25%	0.06
50%	0.11
75%	0.19
max	0.76

Table 7.2: Detailed statistics for the participants of the waiting crowd and the Euclidean distance between participant's initial and end position (table: Kleinmeier, Köster, and Drury 2020, p. 5).

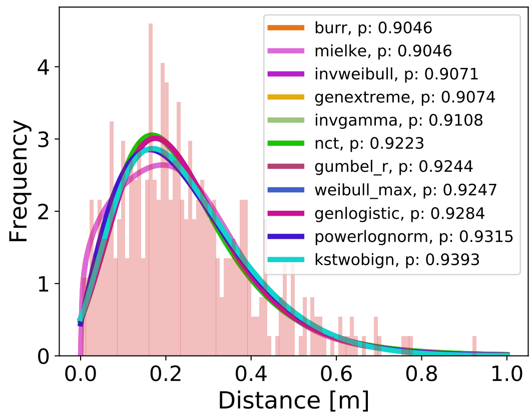


Figure 7.6: The data in red visualizes the maximum Euclidean distance a participant of the waiting crowd moved while the crowd was crossed by the walking participant. The plot includes the best-fitting continuous distributions with a p-value ≥ 0.90 (image: Kleinmeier, Köster, and Drury 2020, p. 5).

	Distances [m] **(metric 2)**
sample size	400.00
mean	0.25
std	0.16
min	0.00
25%	0.13
50%	0.22
75%	0.33
max	0.93

Table 7.3: Detailed statistics for the participants of the waiting crowd and the maximum Euclidean distance (table: Kleinmeier, Köster, and Drury 2020, p. 5).

One can observe that the second metric (maximum Euclidean distance) constantly yields higher values than the first metric. I conclude that participants of the waiting crowd, evade the walking participants (by accepting "long" distances). But, afterwards crowd members tend to return to their original positions. I argue that the data supports a tendency to return, where the mean distance from the initial position is only $0.14\,\mathrm{m}$ with a standard deviation of $0.1\,\mathrm{m}$.

Trajectories of walking participants A third measurement shed light on the trajectories of the walking participants, see Fig. 7.7 and Fig. 7.8. The trajectory plots show that **all** walking participants were able to cross the waiting crowd. Instead of straight lines, one can observe curvy trajectories where walking participants move around a waiting person or both seem to swap places. The measurements of the waiting participants' maximum displacement in Fig. 7.6 show that the waiting participants also move. I argue, that this indicates interaction. In fact, during the experiment one could see different techniques: communication through eye contact or asking verbally, but also shoving the waiting person aside.

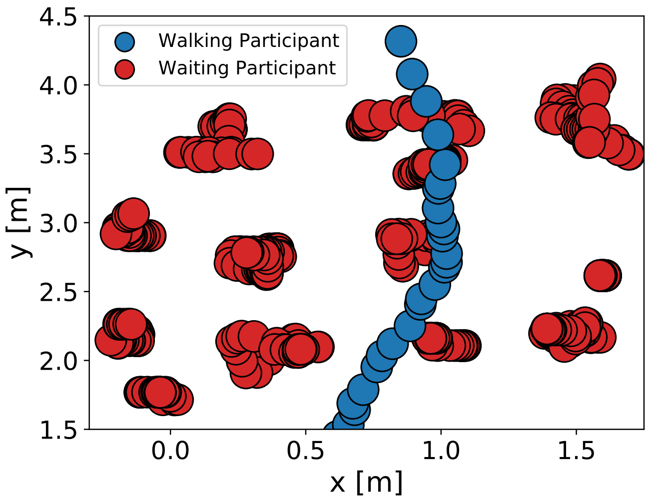


Figure 7.7: The trajectory of a single walking participant inside the waiting area at a time resolution of $1/25\,\mathrm{s}$ (image: Kleinmeier, Köster, and Drury 2020, p. 6).

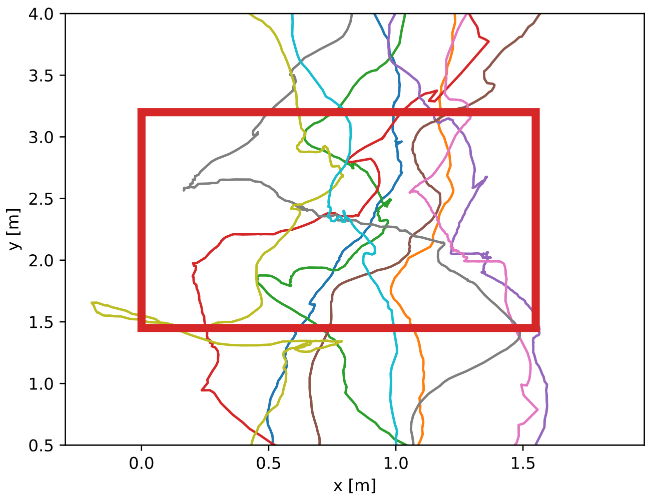


Figure 7.8: The trajectories of ten walking participants inside the waiting area (red rectangle) at a time resolution of $1/25\,\mathrm{s}$ (image: Kleinmeier, Köster, and Drury 2020, p. 6).

Fig. 7.9 visualizes the duration a walking participant spends inside the waiting area. It indicates that the interaction process between the participants takes time. The mean duration of a walking participant's stay inside the waiting area is $7.88\,\mathrm{s}$. Note, that if a walking participant walked through the waiting area, on a straight line, with an instantaneous speed of $0.70\,\mathrm{m/s}$ (measurement from Tab. 7.1), it would only take $\frac{\text{height}}{\text{speed}} = \frac{1.70\,\mathrm{m}}{0.70\,\mathrm{m/s}} = 2.43\,\mathrm{s}$.

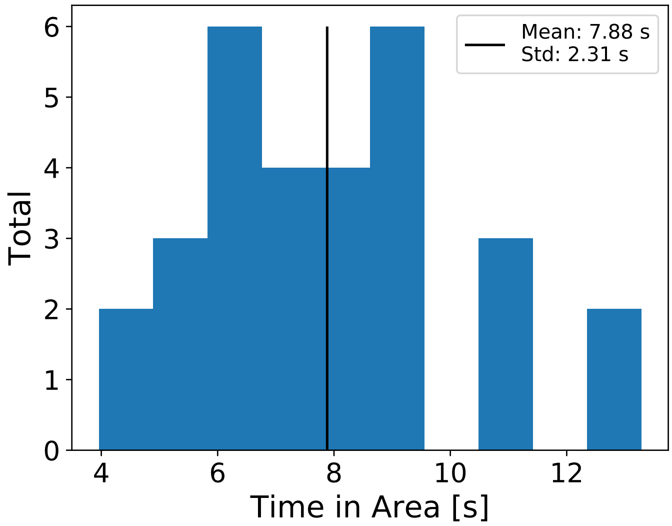


Figure 7.9: The duration of the walking participants inside the waiting area as histogram (image: Kleinmeier, Köster, and Drury 2020, p. 6).

7.1.2 Implementation details

My main conclusion from the experiment is that real humans can pass a dense, waiting crowd but simulated agents can not. The new psychology layer from Sec. 6.1 — with sub-layers perception, cognition and behavior — allows to easily address this shortcoming by breaking down the problem into smaller pieces. There were no environmental stimuli present during the experiment. Therefore, nothing must be implemented on the perception sub-layer. On cognition sub-layer, I must implement the behavioral change from target-oriented agents to cooperative agents which was observed during the experiment. In most pedestrian stream models, agents can only move in a target-oriented way. That is, in each simulation step, agents walk towards a target while repelled by other agents and obstacles. But currently, there is no real interaction between agents outside physical repulsion. This leads to a deadlock situation where no agent can move as we have seen in Fig. 7.1 where a walking agent is blocked by waiting agents. On a cognitive level, we need agents that are able to recognize that they cannot move anymore. Consequently, these agents change their behavior from being (strictly) target-oriented to being cooperative. Cooperative agents are able to swap positions on the locomotion sub-layer. Swapping positions is a very simplistic form of cooperation in a crowding situation but it is sufficient to reenact the experiment qualitatively.

In summary, the generic psychology layer from Sec. 6.1 must be extended by the following aspects:

- Perception: nothing must be done because no environmental stimuli were present during the experiment.

- Cognition: implement class `CooperativeCognitionModel` which sets agent's `Self Category` from `TARGET_ORIENTED` to `COOPERATIVE` when the agent cannot move anymore. Concretely, this means that the speed over the last n steps is below a certain threshold. As threshold I chose $0.05\,\mathrm{m/s}$ which results in almost no movement over the last n steps.
- Behavior: add methods `findSwapCandidate()` and `swapPedestrians()` to class `OSMBehaviorController` and use it during `locmotionModel.update()` if `agent.getSelfCategory() == COOPERATIVE`, where:
  - `findSwapCandidate()` searches the closest neighbor (agent) which is closer to the agent's target.
  - `swapPedestrians()` swaps two agents in the topography.

List. 7.1 and List. 7.2 show how this verbalization is programmed as easy understandable and readable code in Vadere. The code listings also show that it only requires 16 lines of code on cognition layer and 27 lines of code on locomotion layer to utilize the new psychology layer of the Vadere simulator. To ensure correctness of the implementation, the code was developed with a test-driven development strategy resulting in the code coverage which is depicted in Tab. 7.4.

Class name	**Total lines**	**Line coverage [%]**	**Branch coverage [%]**
Note: no perception class required	-	-	-
`CooperativeCognitionModel.java`	16	100	100
`OSMBehaviorController.java`	96	54	50

Table 7.4: The code coverage for the newly introduced classes which are required for the first use case. The code coverage was obtained for Git commit `da89eafa` with the Java code coverage library "JaCoCo" version 0.8.3: https://www.eclemma.org/jacoco/

Listing 7.1: The `update()` method of class `CooperativeCognitionModel` which toggles an agent's self category from target-oriented to cooperative based on agent's speed to reenact the observed behavior from the experiment.

```java
public void update(List<Agent> agents) {

  int lastSteps = 4;
  double threshold = 0.05;

  for (Agent agent : agents) {
    boolean cannotMove = agent.getSpeed(lastSteps) <= threshold;

    if (cannotMove) {
        agent.setSelfCategory(COOPERATIVE);
    } else {
        agent.setSelfCategory(TARGET_ORIENTED);
    }
  }

}
```

Listing 7.2: The `update()` and `updateAgent()` method of the locomotion model which reacts to agent's psychological status reflected by `agent.getSelfCategory()`.

```
public void update(List<Agent> agents, double time) {

  for (Agent agent : agents) {
      updateAgent(agent, time)
  }

}

void updateAgent(Agent agent, double time) {

  selfCategory = agent.getSelfCategory();

  if (selfCategory == TARGET_ORIENTED) {
      makeStepToTarget(agent);
  } else if (selfCategory == COOPERATIVE) {
      // Search for other cooperative agents in a search radius r.
      Agent candidate = findSwapCandidate(agent);

      if (candidate != null) {
          swapPedestrians(agent, candidate);
      } else {
          makeStepToTarget(agent);
      }
  }
  ...

}
```

The operationalization of the observed cooperative behavior from the experiment is depicted as UML activity diagram in Fig. 7.10.

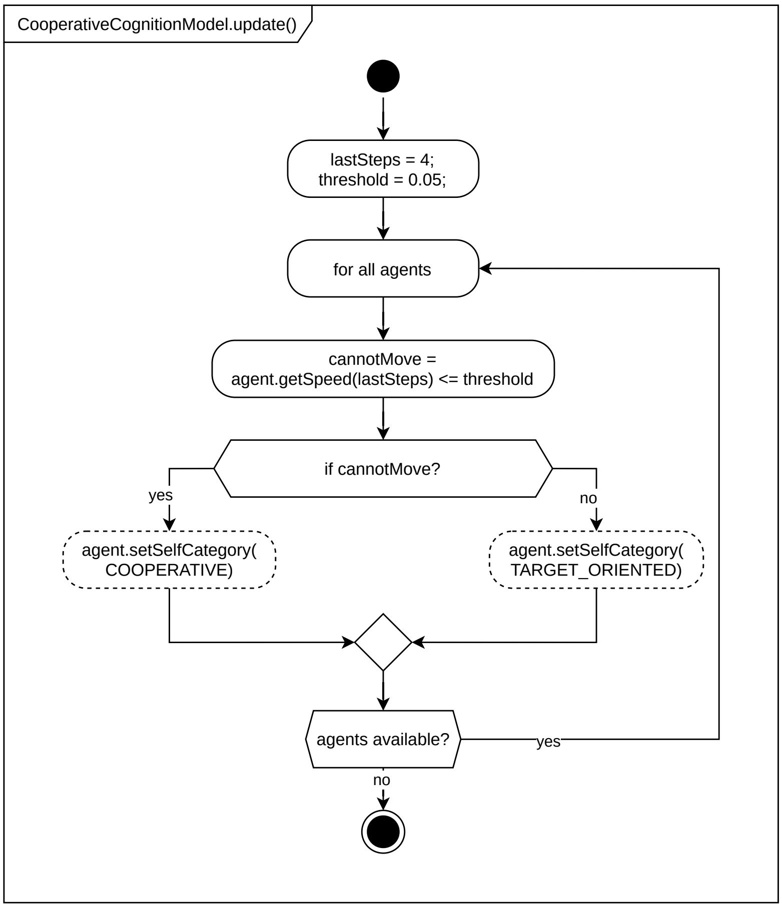


Figure 7.10: The UML activity diagram of the `update()` method of class `CooperativeCognitionModel`.

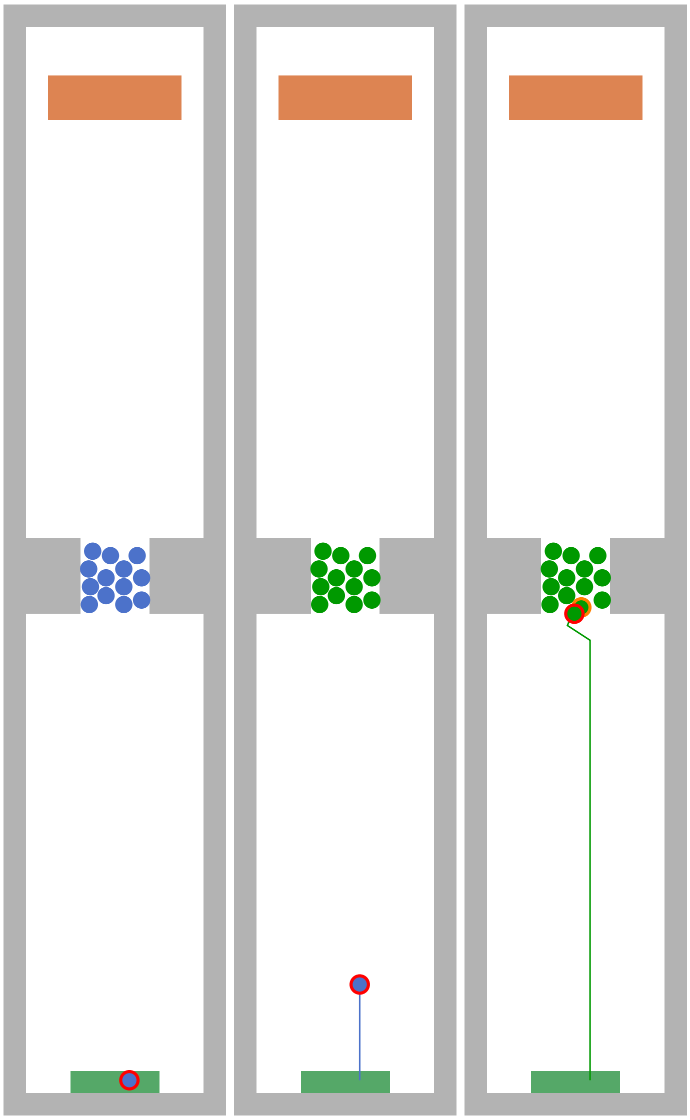
7.1.3 Simulation results and validation

Simulator version and scenario file

The simulations were carried out with Vadere version `1.11` (Git commit hash: `91c1015ef6773f30ea81ab099940bd3b0cf3db09`). The scenario file, which contains all simulation parameters, can be found as PDF attachment (click the icon to save file to disk):

I reenacted the experiment setup from Sec. 7.1.1 as closely as possible by using the same dimensioning. I carried out 100 simulation runs with slightly varying the initial position of the walking agent but consistent positions for the agents of the waiting crowd. Fig. 7.11 and Fig. 7.12 show one of these simulation runs and visualize how the walking agent (red-encircled) changes its target-oriented behavior to a cooperative one when the agent is blocked by the waiting crowd.

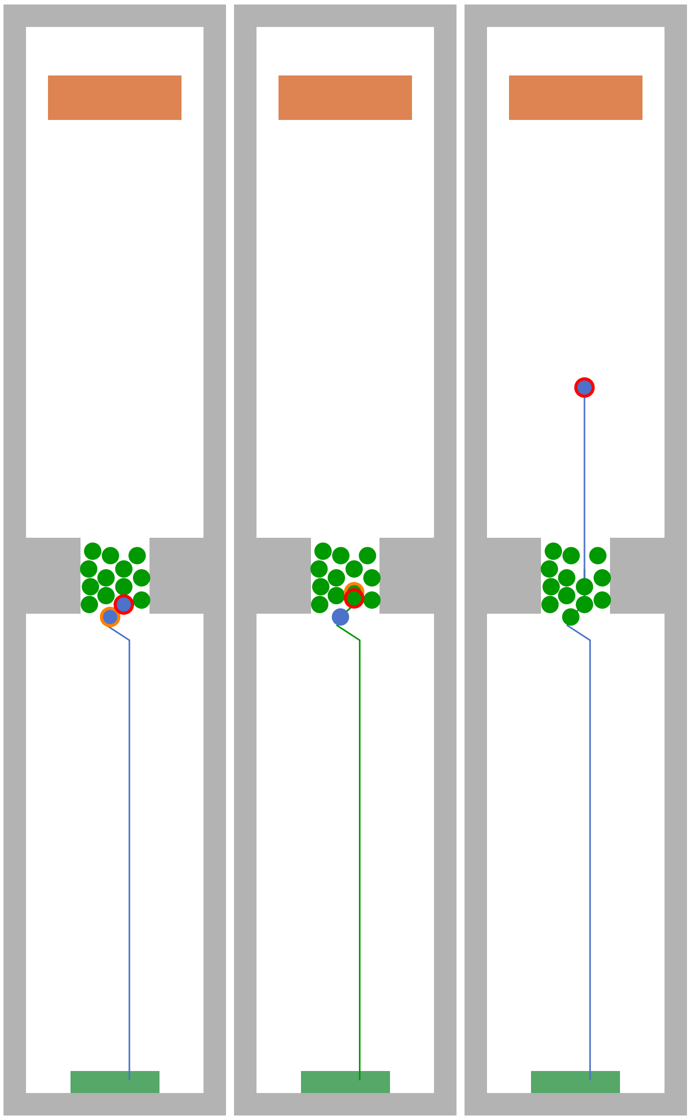
To validate the simulations, I compare the simulation results to the experiment results. In Sec. 7.1.1, I measured the speed of the walking participant, the spatial distribution of the waiting crowd and the trajectories of the walking participant. In the comparison, I



(a) Time step 1 (b) Time step 4 (c) Time step 29

Figure 7.11: A walking agent (red-encircled) starts walking in the green source area and tries to reach the orange target area while the agent is blocked by a waiting crowd consisting of 13 agents. The colors represent the current behavior of an agent: blue is target-oriented behavior and green is cooperative behavior. **(Time step 1)** When the simulation starts, all agents are target-oriented. While the walking agent is attracted by the orange target, the waiting crowd does not have a target and waits. **(Time step 4)** The agents of the waiting crowd become cooperative because their speed falls below a certain threshold. **(Time step 29)** The walking agent reaches the waiting crowd and cannot move anymore. Thus, the walking agent also becomes cooperative. The walking agent searches for a swap candidate (orange-encircled) and both swap positions (image: Kleinmeier, Köster, and Drury 2020, p. 8).

omit the spatial distribution of the crowd because, in the implemented model the agents of the waiting crowd just wait in the waiting area and do not move at all. This is what I assumed as — very simplified — waiting behavior. That is, the traveled distance of the



(a) Time step 31 **(b)** Time step 36 **(c)** Time step 51

Figure 7.12: Cooperative behavior of agents inside the waiting crowd. The colors represent the current behavior of an agent: blue is target-oriented behavior and green is cooperative behavior. **(Time step 31)** After swapping positions, the walking agent (red-encircled) and the swap candidate (orange-encircled) get target-oriented again because their speed is above a certain threshold. **(Time step 36)** The walking agent gets cooperative again and swaps position with another cooperative agent which is closer to the target. **(Time step 51)** The walking agent found its way through the dense crowd by using a cooperative behavior (image: Kleinmeier, Köster, and Drury 2020, p. 9).

agents of the waiting crowd is zero. Therefore, it makes no sense to compare it with the experiment participants who were continuously moving at least a bit.

The 100 simulations reproduce the measured instantaneous "free-flow" speeds at least qualitatively: the walking agents are slowed down inside the waiting area from $1.31\,\mathrm{m/s}$ (outside) to $0.16\,\mathrm{m/s}$ (inside) on average compared to $1.33\,\mathrm{m/s}$ and $0.70\,\mathrm{m/s}$ in the experiment, see Fig. 7.13 and Tab. 7.5.

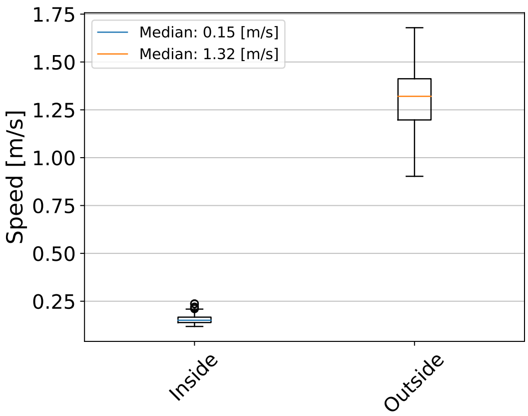


Figure 7.13: Box plot for speed distribution of the walking agent inside and outside the waiting crowd (image: Kleinmeier, Köster, and Drury 2020, p. 9).

	Speed [m/s]	
	inside	**outside**
sample size	100.00	100.00
mean	0.16	1.31
std	0.03	0.15
min	0.12	0.90
25%	0.14	1.20
50%	0.15	1.32
75%	0.17	1.41
max	0.24	1.68

Table 7.5: Detailed statistics for the measured speed distributions of the walking agents inside and outside the waiting crowd (table: Kleinmeier, Köster, and Drury 2020, p. 9).

The speed of the walking agent inside the waiting crowd is much lower than what was observed in the experiment. In the experiment, even if the walking participant is blocked by the waiting crowd for some moments, the walking participant is constantly moving its body a tiny bit. That means the speed of the walking participant is constantly greater than zero. But in the simulation, it takes some simulation steps until a walking agent becomes cooperative when the agent is blocked by the waiting crowd. That is, the agent's speed is zero for a lot of simulation steps which lowers the average speed of the walking agents. Please keep in mind that this is the very first version of such a psychological model of collective cooperation and it will require some sort of calibration in the future.

Nevertheless, in my simulations we see that **all** walking agents were able to cross the waiting crowd like in the experiment with real humans, see Fig. 7.14. Also the mean time of the walking agent inside the waiting area is very close to the experiment observations: $(9.90 \pm 2.24)\,\mathrm{s}$ in simulation compared to $(7.88 \pm 2.31)\,\mathrm{s}$ in the experiment, see Fig. 7.15.

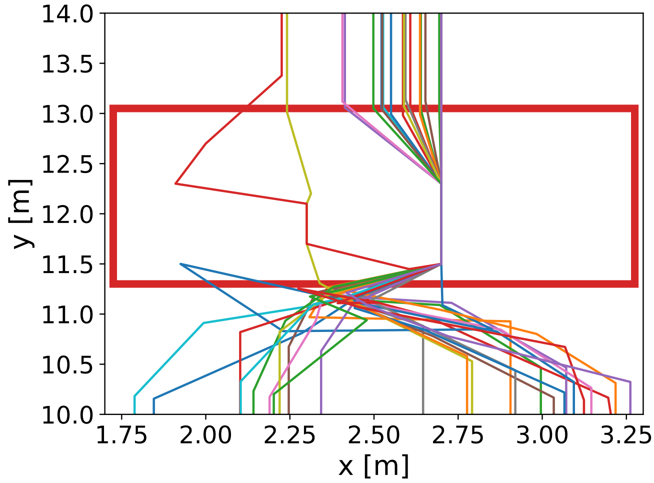


Figure 7.14: The trajectories of 25 walking agents inside the waiting area (red rectangle). Inside the waiting area, the walking agents follow zig-zag trajectories because they swap positions with agents of the waiting crowd. By changing to a cooperative behavior, all walking agents were able to reach the target region. The agents of the waiting crowd are placed at the same positions for all 100 simulation runs. Therefore, we did not see a greater variety of the trajectories inside the waiting area (image: Kleinmeier, Köster, and Drury 2020, p. 9).

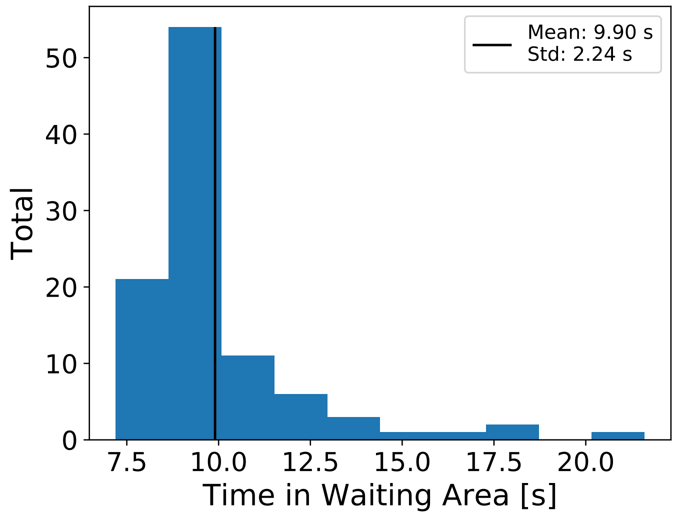


Figure 7.15: The duration of the walking agents inside the waiting area as histogram (image: Kleinmeier, Köster, and Drury 2020, p. 10).

7.2 Use case 2 — Real-world incident: Perceived threat at Oxford Street (London 2017)

This use case represents a real-world incident which contains self-categorization of humans and imitating behavior and is validated qualitatively. The effects of introduced parameters are analyzed in a sensitivity study.

7.2.1 Scenario description

The scenario I use as basis for my implementation of collective behavior and self-categorization occurred at London's underground station Oxford Circus and the nearby streets on Nov 24, 2017, see Fig. 7.16. In retrospective, it can be summarized as false alarm which caused thousands of commuters and shoppers to change their behavior from relaxed walking to scared fleeing.

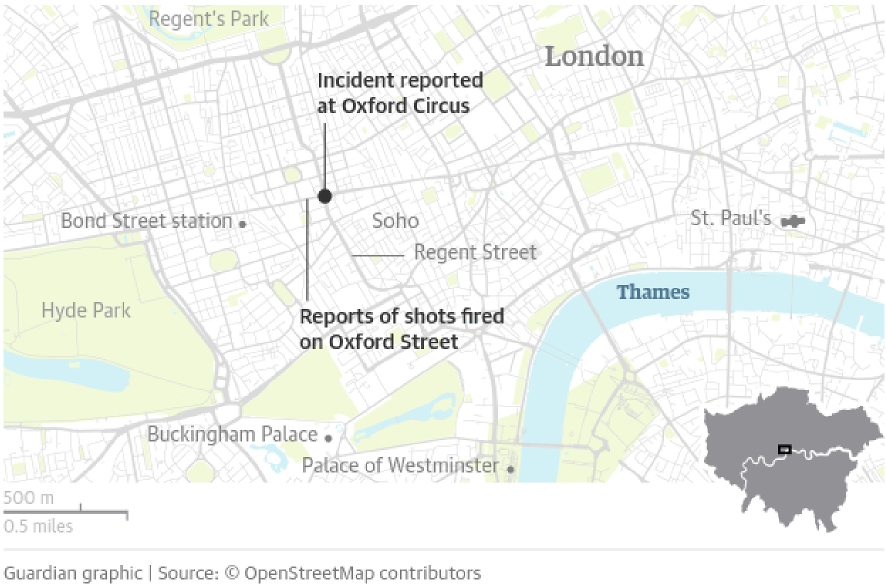


Figure 7.16: Area of interest of the scenario around the underground station Oxford Circus and the nearby Oxford Street in London, 2017 (source: Siddique 2017).

The data that I draw upon comes from a number of sources: three newspaper reports, ten photographs (from newspaper reports), eyewitness accounts (Siddique 2017), two videos (from personal sources) and the official police statements. Especially, personal sources must be seen critical in this context. Thus, data from different types of sources and from different instances was combined. This data triangulation methodology (Denzin 2009) aims to reveal untruth and misleading accounts about the event and to only include accounts that confirm each other. But of course, the data is open to challenge on the basis of representativeness and accuracy. It is very common with such sudden real-life events that quantitative data is very scarce and we mostly have to rely on qualitative data.

The false alarm at Oxford Circus, Nov 24, 2017, occurred at a time of several terrorist attacks in the UK. In 2017, four terrorist attacks in London left 18 dead and 137 injured. A further 22 people were killed by a suicide bomber in Manchester (Greenfield, Cobain, and Dodd 2017). As consequence, the UK terrorism threat level was set to "severe" at that time which means an attack is assessed to be highly likely.

In the following, I describe the events in more detail to draw a picture from the scene. This allows to operationalize the observed behavior and to embed it into the generic architecture described in Sec. 6. The Telegraph summarized the events on the same day (Nov 24, 2017) as following:

> ***Oxford Circus: Met Police end operation after thousands flee in panic over reports of 'gunshots'***
>
> *For a heart-stopping hour, it appeared a nation's collective worst fears had come true.*
>
> *On Black Friday[2] on Britain's best known and busiest street, packed with Christmas shoppers, commuters and school children, it seemed that terrorists had struck. At 4.37pm, hordes of people on Oxford Street were convinced they had heard the sound of gunfire and explosions.*
>
> *It was a false alarm, but whatever they heard — or for that matter didn't hear — prompted a stampede for cover. Shoppers ran for their lives, certain they were under attack.*
>
> (Mendick and Yorke 2017)

The Guardian provided more details in an article one day after the events (Nov 25, 2017):

> ***Oxford Street panic began with fight at tube station, suggest police***
>
> *Visitors to London West End ran and hid, two tube stations were closed and armed police raced to scene after incident*
>
> (Greenfield, Cobain, and Dodd 2017)

Also the Evening Standard agreed on the false alarm: "Oxford Circus: Terror alert on London's busiest shopping street declared false alarm" (Collier and Grafton-Green 2017).

The chronology of the events from The Guardian draws the big picture of the scenario:

- *Armed police and officers from British Transport Police rushed to the scene shortly after 4.30pm, after numerous calls of shots fired on Oxford Street and at Oxford Circus tube station, responding, as if the incident is terrorist related.*
- *Panicked commuters and shoppers ran out of the tube station and took cover in shops, on one of the busiest shopping days of the year — Black Friday — as rumours circulated about what had occurred. People were advised to avoid the area or stay inside if already there.*
- *British Transport Police said one woman received a minor injury in the crush as she fled Oxford Circus tube station [Later, nine people were reported injured (Greenfield, Cobain, and Dodd 2017)].*
- *Shortly after 6pm, the Met said its response had been stood down. In a statement, it said the first armed response vehicle was on the scene in less than one minute from receiving the first call.*

(Siddique 2017)

An eyewitness account below supports the chaotic situation and Fig. 7.17 provides an impression of the atmosphere at the scene.

[2] "The Friday immediately following Thanksgiving Day that is considered by retailers to mark the beginning of the holiday shopping season." (Merriam-Webster. (n.d.). Black Friday. In Merriam-Webster.com dictionary. Retrieved January 7, 2021, from https://www.merriam-webster.com/dictionary/Black%20Friday)

(a) Source: Reuters **(b)** Source: EPA **(c)** Source: AFP/Getty Images

Figure 7.17: Scenes at Oxford Street in 2017: **(a)** People run down Oxford Street following reports of shots being fired. **(b)** Armed London police officers react to the incident. **(c)** Armed police patrol near Oxford street as they respond to the incident. (images: Collier and Grafton-Green 2017)

The eyewitness describes the unfolding of the events as following (Siddique 2017):

> *I was just near Oxford Circus on the corner of Regent's street on the way back to tube. I could see some police had just arrived but I thought maybe it was for traffic control because it was so busy.*
>
> *Then suddenly people started screaming and running dropping their bags. I just started running too. There were hundreds and hundreds of people running away. Some said someone had been stabbed, others were saying shots fired, everyone was really scared.*
>
> *People were really really panicked and shops were instantly locking their doors. I just kept going till I got to Regent's Park.*

But, what can also be derived especially from the video material and the images: not all people fled immediately. Instead, some were attracted by the perceived threat at Oxford Circus and headed towards the apparent bang. Others obviously did not trust the fleeing people and continued walking their way, see Fig. 7.18 p. 119.

7.2.2 Implementation details

After studying the accounts about the false alarm at Oxford Street in 2017, it is important to distill what is crucial from a modeling perspective to operationalize the observed behavior. Previous modeling publications, e. g. Pelechano, O'Brien, et al. 2005, simply mentioned they modeled "panic behavior". But, panic is a very fuzzy and imprecise term and it does not describe what really happens! In 2005, the sociologists Schweingruber and Wohlstein tried to uncover crowd myths which are often picked up by the crowd modelers like "panic behavior" (Hirai and Tarui 1975; Helbing, Farkas, and Vicsek 2000; Pelechano, O'Brien, et al. 2005; Schneider 2010; Frank and Dorso 2011). Often, modelers draw upon myths like "panic behavior" because they do not have a sociology or psychology background. But in (Schweingruber and Wohlstein 2005, p. 138), the authors clearly demystified the term "panic":

> *A leading example of supposed irrational crowd behavior is "panic" which is generally conceptualized as irrational flight in which fearful people may end*

(a) Source: Reuters (I highlighted fleeing people in red and walking people in blue)

(b) Source: Reuters (I highlighted fleeing people in red and walking people in blue)

Figure 7.18: Mixed reactions to the perceived threat at Oxford Circus: while some people fled immediately (red outline), others continued walking their way with hands in their pockets or continued making phone calls (blue outline).

> *up hurting or even killing themselves and others. Subsequent research has not demonstrated that people in crowds suffer any cognitive deficits. Indeed, research into emergency dispersal (e.g., Bryan 1982; Canter 1980; Johnson 1987a, 1987b; Johnson and Johnson 1988; Keating 1982; Sime 1980, 1995) has consistently shown that when people are fleeing from dangerous situations they are guided by social relationships and roles and exhibit altruistic behavior.*

From the scenario description we know that an environmental stimulus (a bang) at underground station Oxford Circus caused people to run away. They accelerated and searched for a safe zone. Bystanders and other pedestrians, which approached the underground station Oxford Circus from all directions, imitated the escaping behavior, but not all. Some pedestrians continued walking their way and ignored the escaping people. Newer psychological researches suggest that imitation is a too simple concept and a more complex process of social appraisal leads to collective behavior (Bruder, Fischer, and Manstead 2014). Yet, to keep the model as simple as possible in the first place, I stick to the observed "imitating" behavior.

In summary, the generic psychology layer from Sec. 6.1 must be extended by the following aspects:

- Perception: implement class `Threat`. A `Threat` can be a loud bang like at Oxford Circus or any other environmental cue. A `Threat` has a loudness and a radius in which the threat can be perceived acoustically or visually. For instance, a loud bang can frighten people while a quiet whistle can attract people. These attributes allow great flexibility and variation.
- Cognition: implement class `ThreatCognitionModel` which varies agent's `SelfCategory` between `TARGET_ORIENTED`, `THREATENED` and `COMMON_FATE`. This fulfills two observed behaviors:
  1. Agents which perceived the `Threat` escape. That is, when being `THREATENED`, the agents maximize the distance to the `Threat` origin and they accelerate. Additionally, after reaching a certain distance from the `Threat`, agents share a `COMMON_FATE` and search for a safe zone. Safe zones are targets which are placed sufficient far away from the `Threat` origin.
  2. Agents which did not perceive the `Threat` themselves but see other agents escaping have two options:
     - Either trust the fleeing agents and imitate their behavior.
     - Or do not trust the fleeing agents and stay `TARGET_ORIENTED`.
       This is where self-categorization and group membership comes into play and is crucial for realistic behavioral changes and collective behavior. Psychologically, two agents who trust each other form an in-group. Two agents who do not trust each other are out-group to each other. If an unthreatened agent *A1* has the `GroupMembership` `IN_GROUP` and *A1* perceives another escaping `IN_GROUP` member *A2*, *A1* imitates the escaping behavior of *A2*. In contrast, if the unthreatened agent has the `GroupMembership` `OUT_GROUP`, the agent ignores the behavior of other agents and stays `TARGET_ORIENTED`.
- Behavior: add two methods to class `OSMBehaviorController`. The first method is `changeToTargetRepulsionStrategyAndIncreaseSpeed()` as reaction to the cognitive result `agent.getSelfCategory() == THREATENED`. The second method is `changeTargetToSafeZone()` if `agent.getSelfCategory()== COMMON_FATE`.
  - `changeToTargetRepulsionStrategyAndIncreaseSpeed()`: in this case, an agent perceives a `Threat` and wants to maximize the distance to the `Threat`. In the optimal steps model, agents usually find their next position by minimizing the travel time to a target: points closer to a target have a shorter travel time than far-away points. This method just negates the sign of the target travel times. By using this simple technique, the original minimization problem of the optimal steps model is preserved and, during locomotion, agents maximize the distance to a former target. That is, agents search for

points which are further away from a target in the minimization phase. Additionally, this method doubles an agent's preferred speed as reaction to the `Threat`. Doubling the speed is just a simple assumption because quantitative data is missing for the Oxford Street scenario.

- `changeTargetToSafeZone()`: this method reacts to the `agent.getSelfCategory() == COMMON_FATE` condition. After the immediate fear response to the threat, that is fleeing, the people at Oxford Street searched cover in shops. To reflect this, after reaching a certain distance to the `Threat`, agents start searching for a safe zone. To this end, an agent selects the target as safe zone which is closest to the agent's source. This is in alignment with place attachment theories (Scannell and Gifford 2010; Rollero and De Piccol 2010). In dangerous situations, humans tend to escape to familiar places (or where they came from). Clearly, where the place attachment theory falls down in the Oxford Street incident is that some of the people were tourists and some did not live or work in the area. That is, they are not familiar with the location. Therefore, I assume the area that is close to an agent's source as safe zone.

This simple operationalization reflects the observed behavior from the scenario description. The operationalization combines knowledge from

- psychology of decision-making: the perception[3] and cognitive processing of a threat which lead to a behavioral change of agents
- social psychology: self-categorization which leads to collective behavior across in-group members
- the reusable architecture from Sec. 6

The following UML activity diagrams Fig. 7.19–7.22 depict the exact implementation steps for the class `ThreatCognitionModel` to obtain short, readable and testable methods. The code was developed with a test-driven development strategy resulting in the code coverage in Tab. 7.6.

Class name	**Total lines**	**Line coverage [%]**	**Branch coverage [%]**
`SimplePerceptionModel.java`	55	100	92
`ThreatCognitionModel.java`	53	92	77
`OSMBehaviorController.java`	96	54	50

Table 7.6: The code coverage for the newly introduced classes which are required for the second use case. Please note that the test code for `SimplePerceptionModel.java` only covers the true condition of an `if` statement, but misses the branch if the condition is false. This approach results in 100% line coverage but only 92% branch coverage. The code coverage was obtained for Git commit `da89eafa` with the Java code coverage library "JaCoCo" version 0.8.3: https://www.eclemma.org/jacoco/

[3]The perception of the threat, a loud bang, is psychologically grounded in the signal detection theory, see Sec. 3.2 on p. 62.

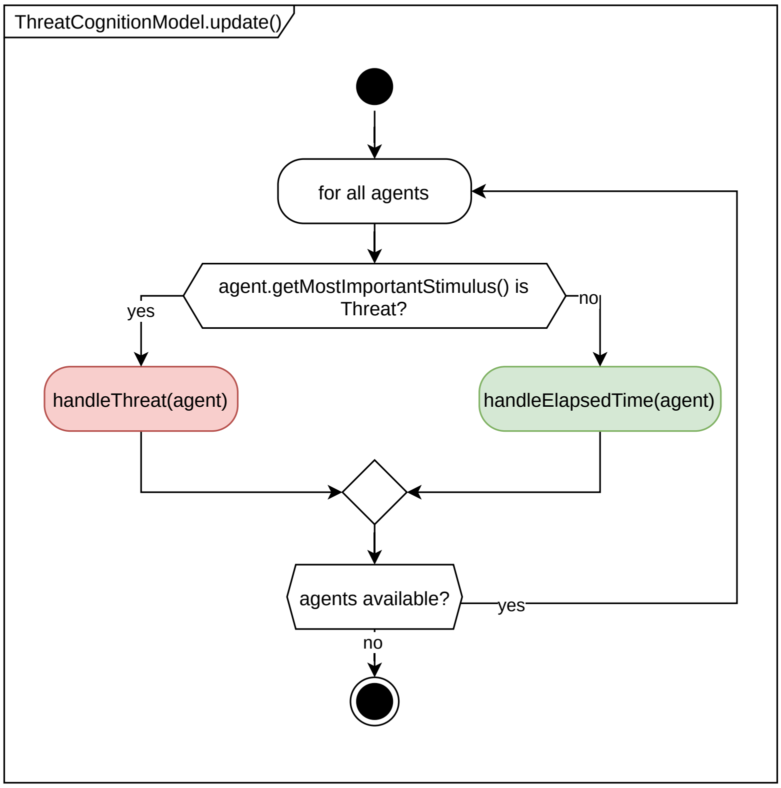


Figure 7.19: `ThreatCognitionModel.update()`: the entry point of the cognitive process. The code tests if an agent perceived a threat. If so, it calls the `handleThreat()` method. Otherwise, it calls `handleElapsedTime()` to move an agent.

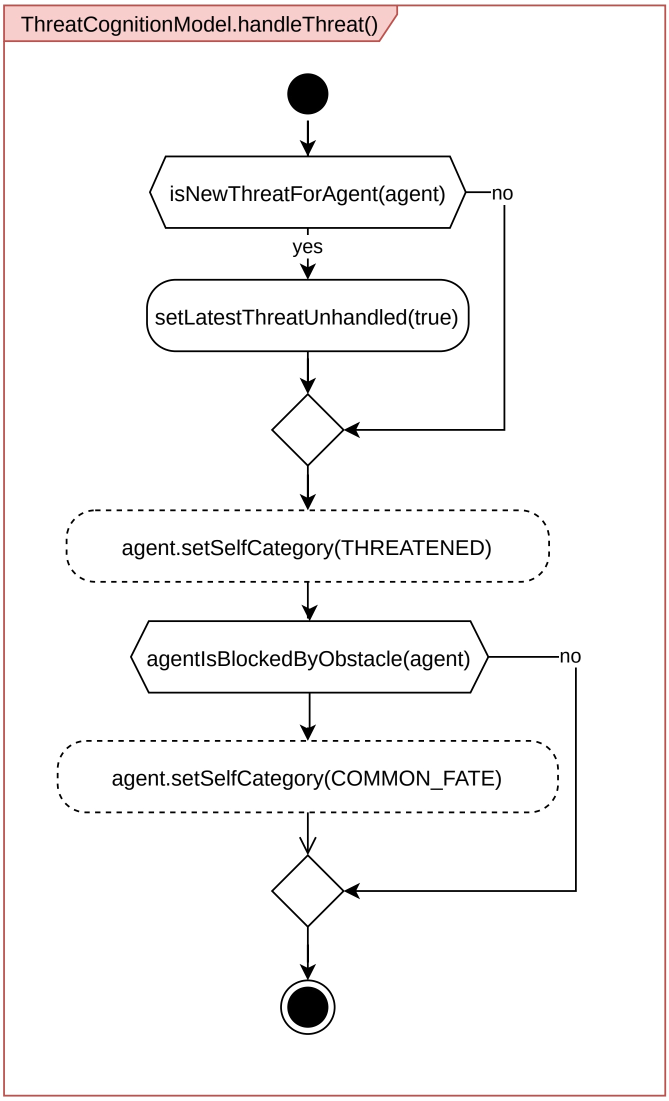


Figure 7.20: The UML activity diagram of the `handleThreat()` method of class `ThreatCognitionModel`: the purpose of this method is to signal to the locomotion layer that the agent is threatened. This method must handle two corner cases: **(1)** Agents shall accelerate when they perceive a `Threat`. But, this acceleration should only happen once. Therefore, the method tests for `isNewThreatForAgent()`. **(2)** The implementation uses the optimal steps model as locomotion model. When agents maximize the distance to the `Threat`, it could happen that agents are blocked by obstacles and agents do not navigate around them because of blindly trying to maximize the distance to the threat. In this case, agents should immediately search for a safe zone allowing them to better maneuver around obstacles. In all other cases, it is sufficient to finish the cognitive process with `THREATENED` and react accordingly on the locomotion layer (with: maximize distance to the threat and accelerate).

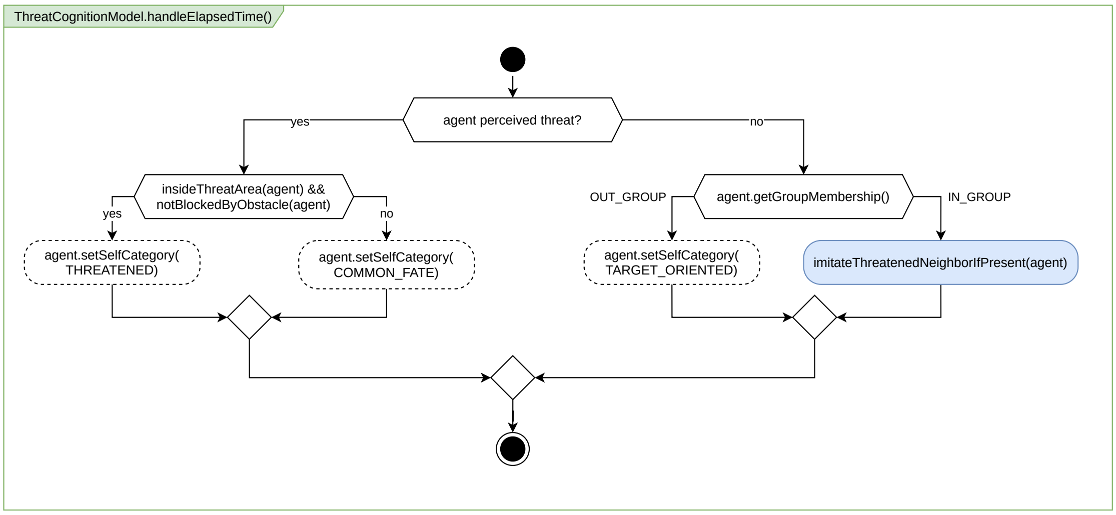


Figure 7.21: The UML activity diagram of the `handleElapsedTime()` method of class `ThreatCognitionModel`: this cognitive process has the following purposes. If the agent perceives a threat, test if the agent is still inside the threat area (result: `THREATENED`) or outside (result: `COMMON_FATE`). If the agent does not perceive a threat, either keep behavior `TARGET_ORIENTED` or imitate behavior if another in-group member was perceived by calling `imitateThreatenedNeighborIfPresent()`.

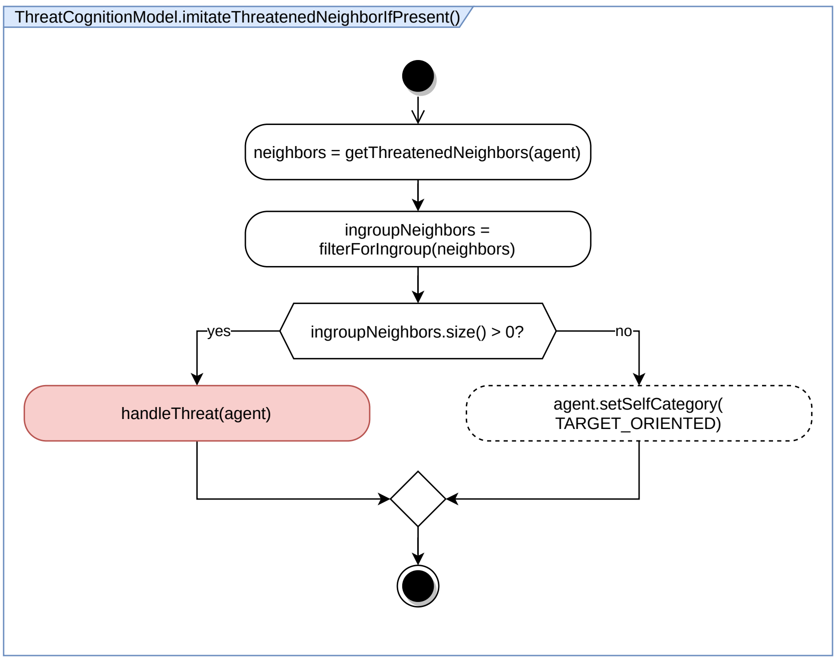


Figure 7.22: The UML activity diagram of the `imitateThreatenedNeighborIfPresent()` method of class `ThreatCognitionModel`: this cognitive process looks for threatened in-group neighbors and imitates their behavior by reusing method `handleThreat()`.

Implementation remark: A wrapper class for an easy GUI integration Vadere has originally been designed as a framework to compare locomotion models. To this end, Vadere defines an interface `Model` which a locomotion model must implement so that Vadere can automatically visualize all model parameters in its GUI and to carry out the simulation loop (List. 6.1, p. 89). The implementation of the perceived threat scenario introduces a new parameter which is called `probabilityIngroupMembership`. To make this parameter easily accessible for GUI users, a new `Model` `SelfCatThreatModel` is implemented which holds `AttributesSelfCatThreatModel` which in turn stores the `probabilityIngroupMembership`. See Fig. 7.23 how Vadere visualizes the `Model` parameters in its "Model" tab.

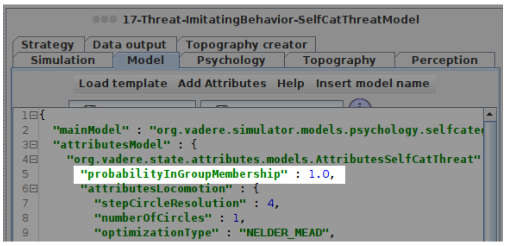
```
public class SelfCatThreatModel
    implements Model {

    // Variables
    private AttributesSelfCatThreat
        attributesSelfCatThreat;
    ...
}

public class AttributesSelfCatThreat
    extends Attributes {

    AttributesOSM attributesLocomotion
        = new AttributesOSM();
    double probabilityInGroupMembership
        = 0.0;
    ...
}
```

(a) The wrapper class `SelfCatThreatModel`.



(b) The "Model" tab in the GUI.

Figure 7.23: Vadere visualizes the `probabilityIngroupMembership` parameter of the wrapper class `SelfCatThreatModel` **(a)** under the "Model" tab **(b)**.

7.2.3 Simulation results and validation

Simulator version and scenario file

The simulations were carried out with Vadere version `1.15` (Git commit hash: `ab19352993746cd0662ad8ac7cf910ce6d48a683`). The scenario file, which contains all simulation parameters, can be found as PDF attachment (click the icon to save file to disk):

In this section, I walk the reader through the simulation results of the perceived threat scenario step by step. Firstly, I show how I import OpenStreetMap data (OpenStreetMap contributors 2020) to match the scene at Oxford Circus as accurately as possible. Then, I depict some simulation steps using a bird's eye view and magnified views to visualize how the behavioral changes of agents evolve over time. Lastly, I conclude with a short parameter study which evaluates the effects of the newly introduced parameter `probabilityInGroupMemberhsip` on the evacuation time.

The simulation area Fig. 7.24, p. 127, visualizes the simulation area with a size of $402.0\,\mathrm{m} \times 369.0\,\mathrm{m}$ (width $\times$ height). The simulation area is centered around the underground station Oxford Circus which was the initial scene for the perceived threat. To reenact the scene as accurately as possible, a self-written Python script imports map material around Oxford Circus from OpenStreetMap. The Python script converts OpenStreetMap buildings to Vadere obstacles.

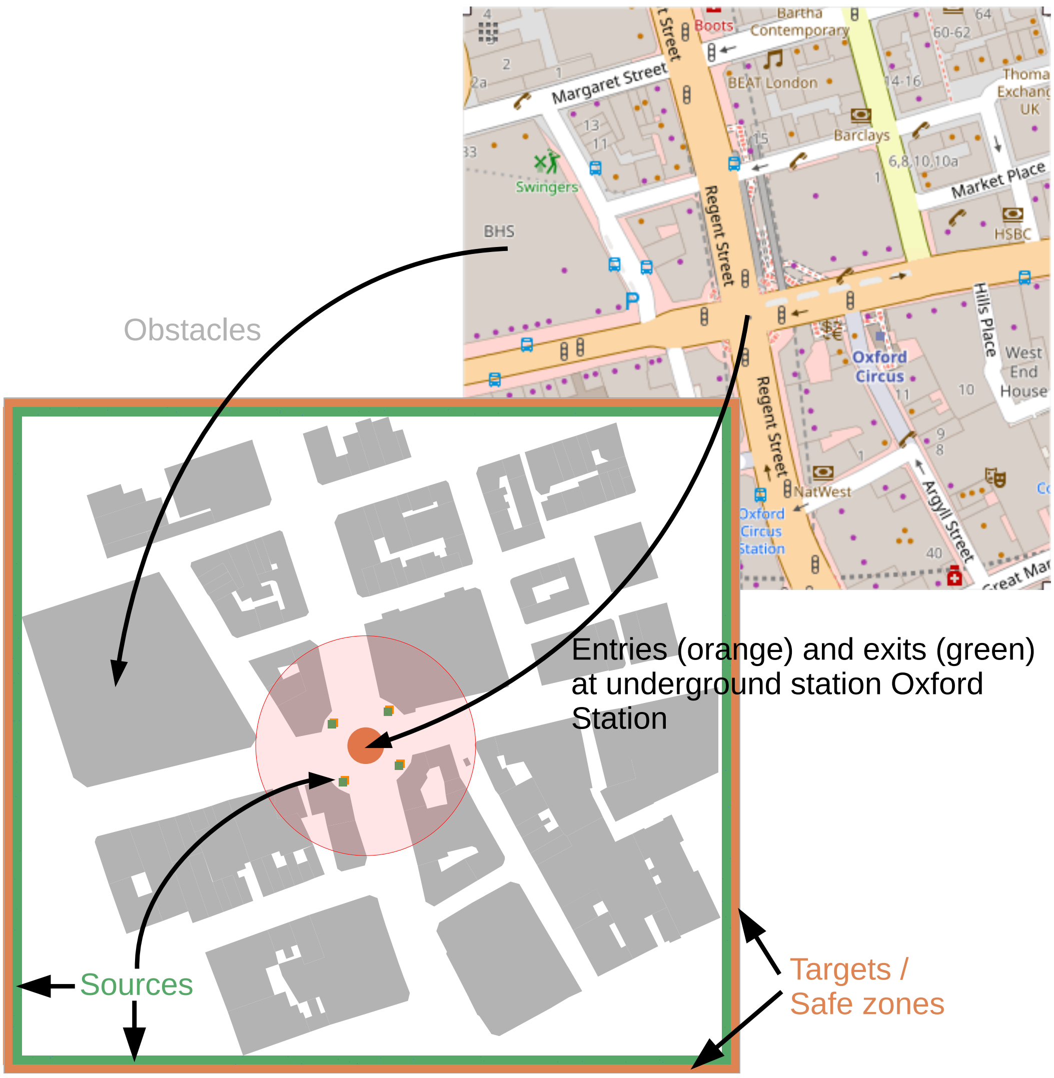


Figure 7.24: The simulation area in OpenStreetMap (background) and Vadere (foreground). A self-written Python script imports the buildings from OpenStreetMap as obstacles (gray) into Vadere. Additionally, the following Vadere scenario elements are added for a realistic simulation: **(1)** Four sources (green) at the underground station Oxford Circus for agents that leave the underground station at north, south, west or east exit. **(2)** Four sources (green) at the top, bottom, left and right edge so that agents can approach the underground station from all directions like observed in the real world. **(3)** Four targets (orange) which represent safe zones after agents perceive a threat. **(4)** A threat (orange) at the center of Oxford Circus which appears 60 seconds after the simulation has started and which can be perceived in a radius of 60 meter (as light shade of red).

Together with obstacles, following Vadere scenario elements are added for a realistic simulation (see Fig. 7.24): **(1)** Four sources (green) at the underground station Oxford Circus for agents that leave the underground station at north, south, west or east exit. **(2)** Four sources (green) at the top, bottom, left and right edge so that agents can approach the underground station from all directions like observed in the real world. **(3)** Four targets (orange) which represents safe zones after agents perceive a threat. **(4)** A threat (orange) at the center of Oxford Circus which appears 60 seconds after the simulation started and which can be perceived in a radius of 60 meter (depicted as light shade of red). It is assumed that agents use the underground exit that corresponds to their destination. For instance, agents heading southwards take the southern exist and agents heading northwards take the northern exit. But, in real life it can be observed that this idealization is not always true and humans take “wrong” exits accidentally or also intentionally. To account for this, I use Vadere’s `TargetChanger` to change the original destination of agents. For example at the southern exit, 30% of the agents are redirected by the `TargetChanger` (10% northwards, 10% westwards and 10% eastwards). This technique is used for all four exits at the underground station, see Fig. 7.25.

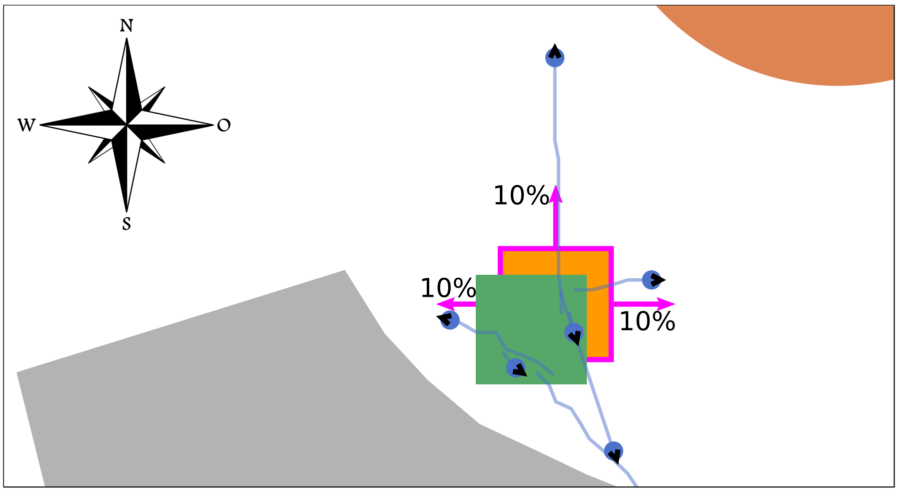


Figure 7.25: A `TargetChanger` (pink outline) redirects 30% of the agents to other directions. For example, 30% of the agents at the southern exit are redirected north-, west- and eastwards. 70% of the agents at the southern exit are heading southwards.

In the following four sections, I will focus on small subareas of the simulation area to exemplify the behavioral changes of agents over time. Fig. 7.26, p. 129, highlights the four areas of interest in the whole simulation area. In the first area of interest, we see how agents behave in a target-oriented way after leaving the underground station. In the second area, we see how agents react to the perceived threat at the underground station by maximizing the distance to the treat. In the third area, we see how agents change their behavior to searching for a safe zone after leaving the area of immediate threat. The fourth area depicts how in-group members (agents) imitate escaping behavior. For the simulation the newly introduced parameter “probabilityGroupMembership” was set to 0.8 (80%) and agents used a “searchRadius” of $5.0\,\mathrm{m}$ to search for in-group members. All other simulation parameters were left to default values.

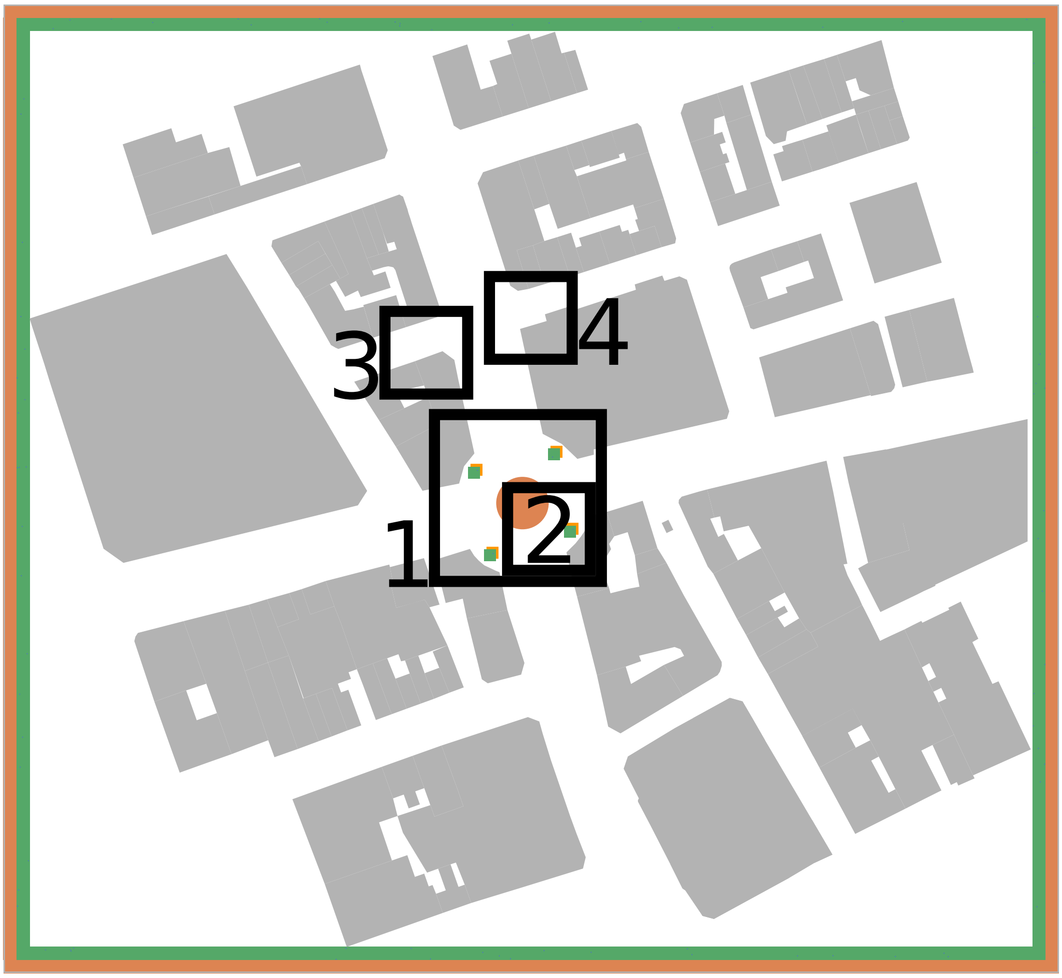
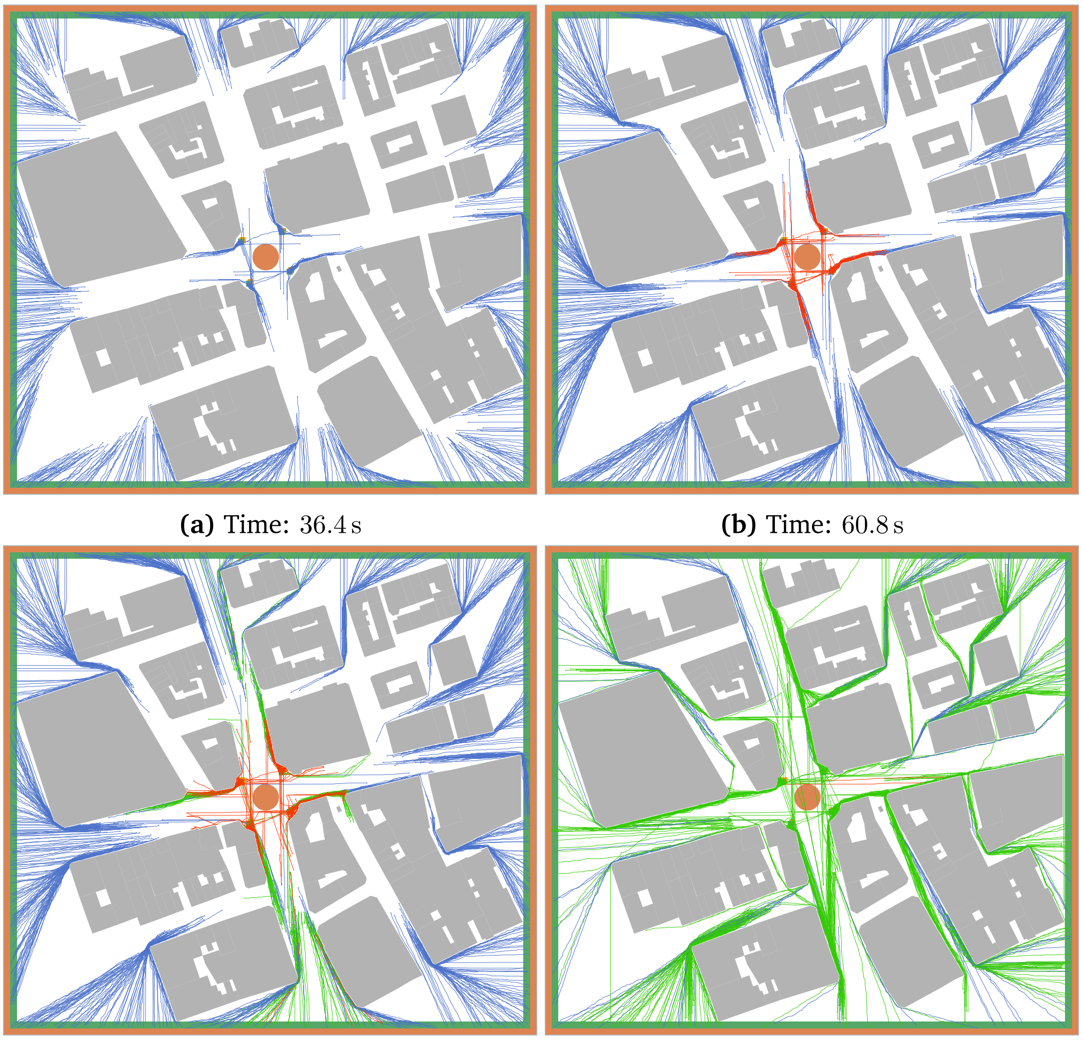


Figure 7.26: An overview of subareas of the whole simulation area which will be examined in more detail in the following sections. **(1)** Subarea 1 focuses on target-oriented agents. **(2)** Subarea 2 shows how target-oriented agents react to the threat. **(3)** Subarea 3 shows how threatened agents start searching for a safe zone. **(4)** Subarea 4 focuses on imitating behavior.

Bird's eye view



(a) Time: 36.4 s

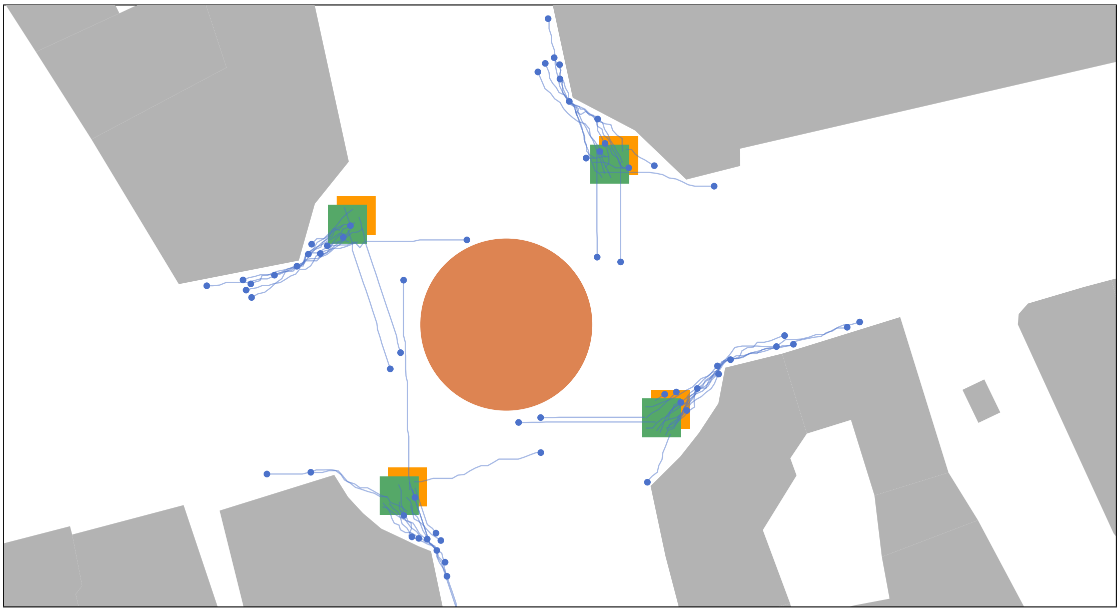
(b) Time: 60.8 s

(c) Time: 70.4 s

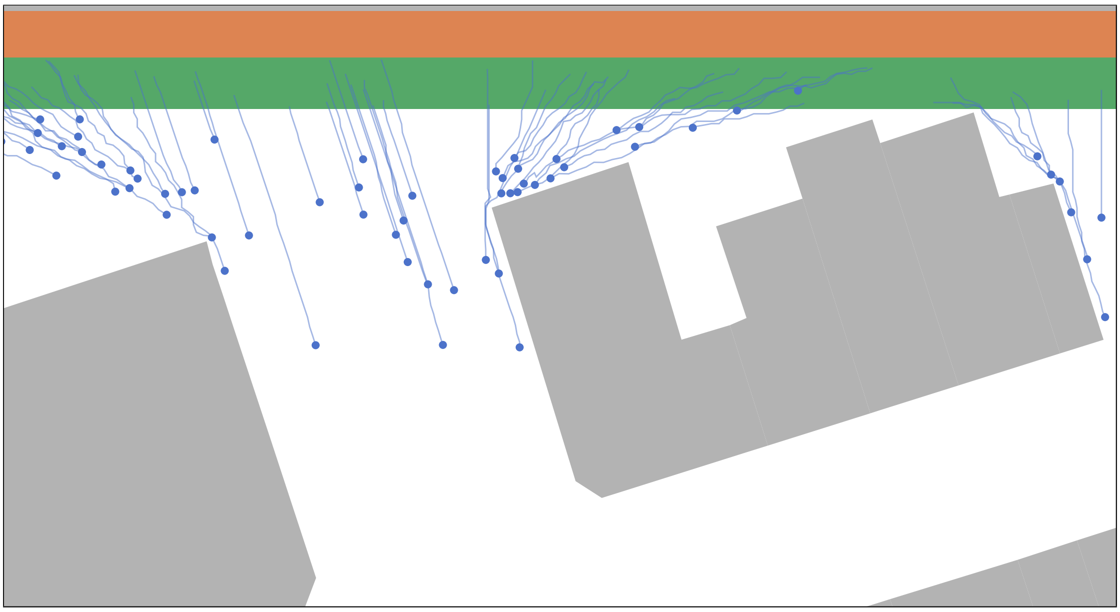
(d) Time: 132.4 s

Figure 7.27: Birds eye view of a simulation of the perceived threat at underground station Oxford Circus and the behavioral changes of agents. The colored lines represent the agents' trajectories and their current self category: blue = target-oriented, red = threatened, green = common fate. **(a)** After the simulation starts, agents leave the underground station Oxford Circus and, simultaneously, agents head towards the underground station from all directions. **(b)** After 60 s, a threat occurs at the underground station which is perceived by agents denoted in red. **(c)** The threatened agents escape and leave the threatened area which is indicated by the green color. **(d)** After 132 s, most of the agents have escaped and the fleeing agents "inform" other agents which did not perceive the threat themselves. Only a few agents are left uninformed and are still walking towards the underground station (blue trajectories).

Magnified view: Simulation start

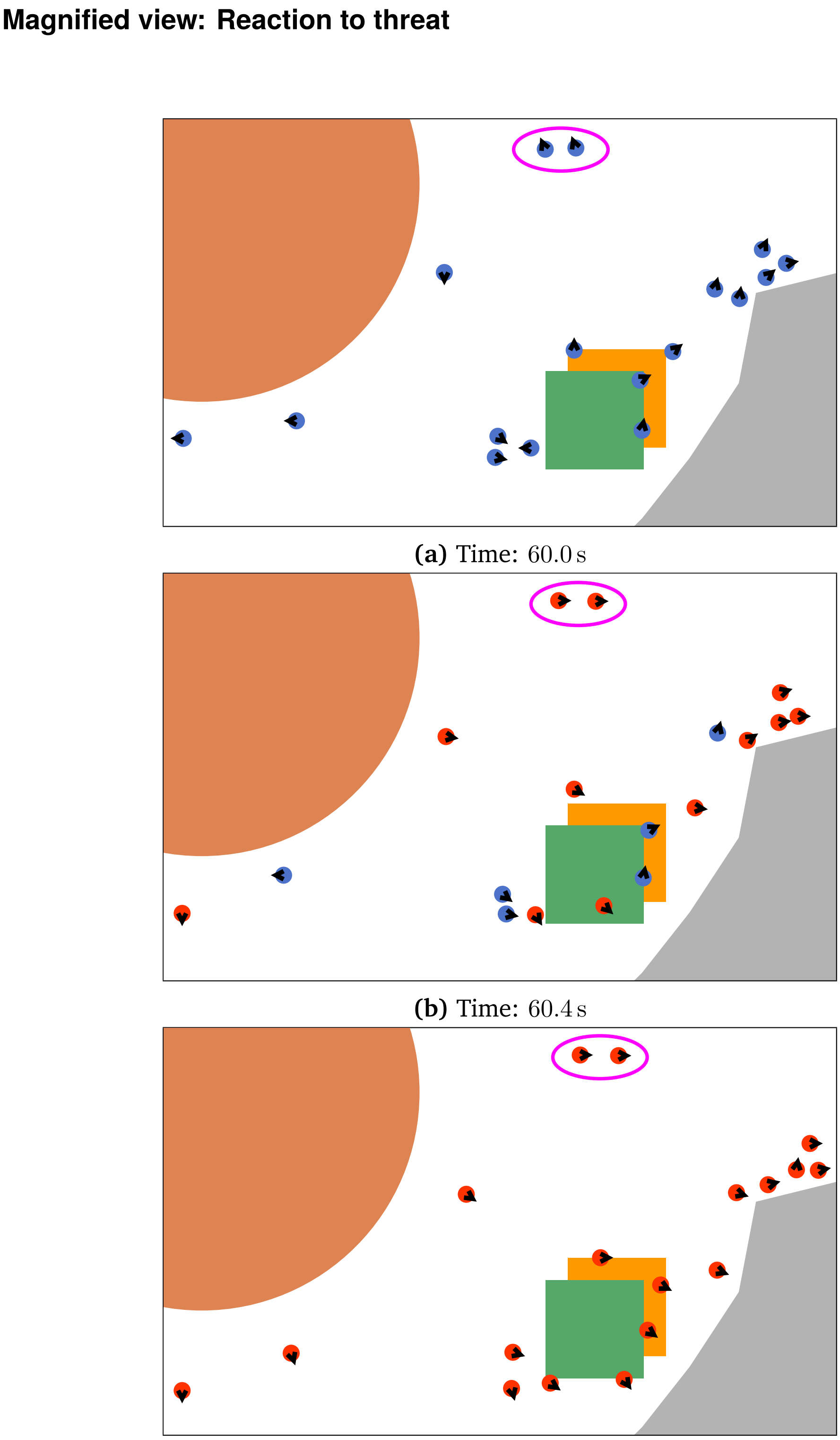


(a) Time: 16.0 s (central area)



(b) Time: 16.0 s (northern area)

Figure 7.28: Magnified view of the central and the northern part of the simulation area shortly after the simulation started. **(a)** Agents leave the underground station Oxford Circus. **(b)** Agents walk towards the underground station.



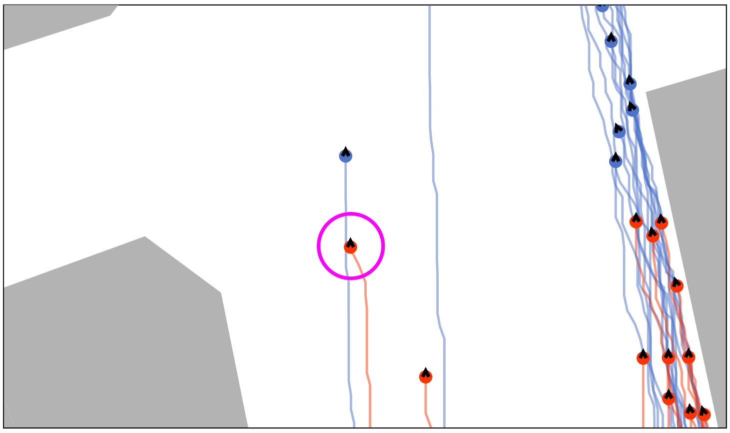
(a) Time: 60.0 s

(b) Time: 60.4 s

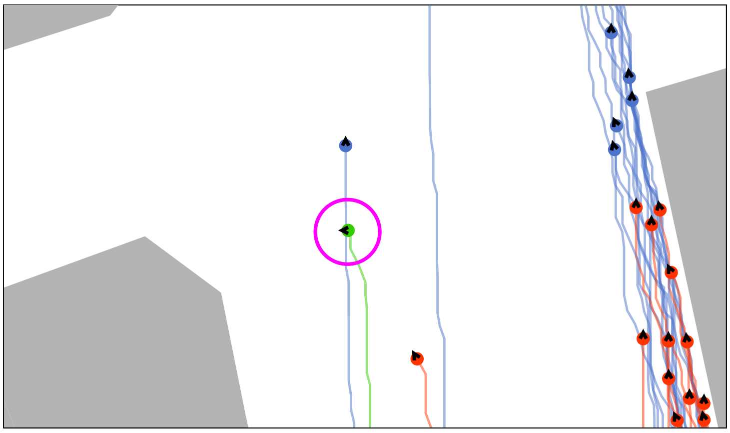
(c) Time: 60.8 s

Figure 7.29: Magnified view of the agents' reaction to the threat. Agents (in the purple ellipsis) maximize the distance to the threat and accelerate. Small triangles indicate the changing walking direction of agents after perceiving the threat. **(a)** to **(c)** shows agents which change their behavior from `TARGET_ORIENTED` (blue) to `THREATENED` (red).

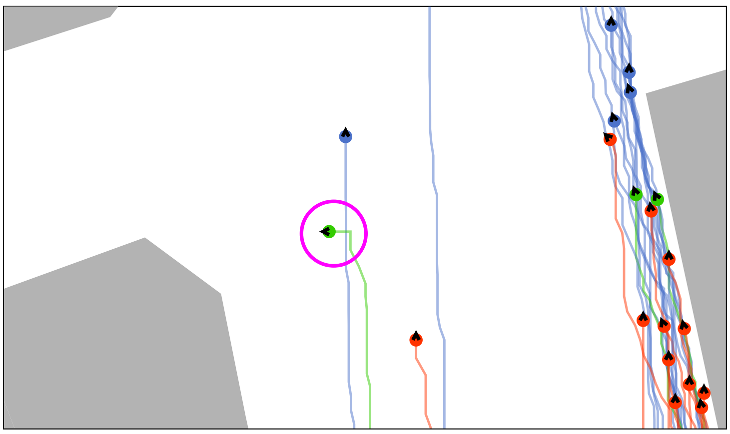
Magnified view: Searching for a safe zone



(a) Time: 61.2 s



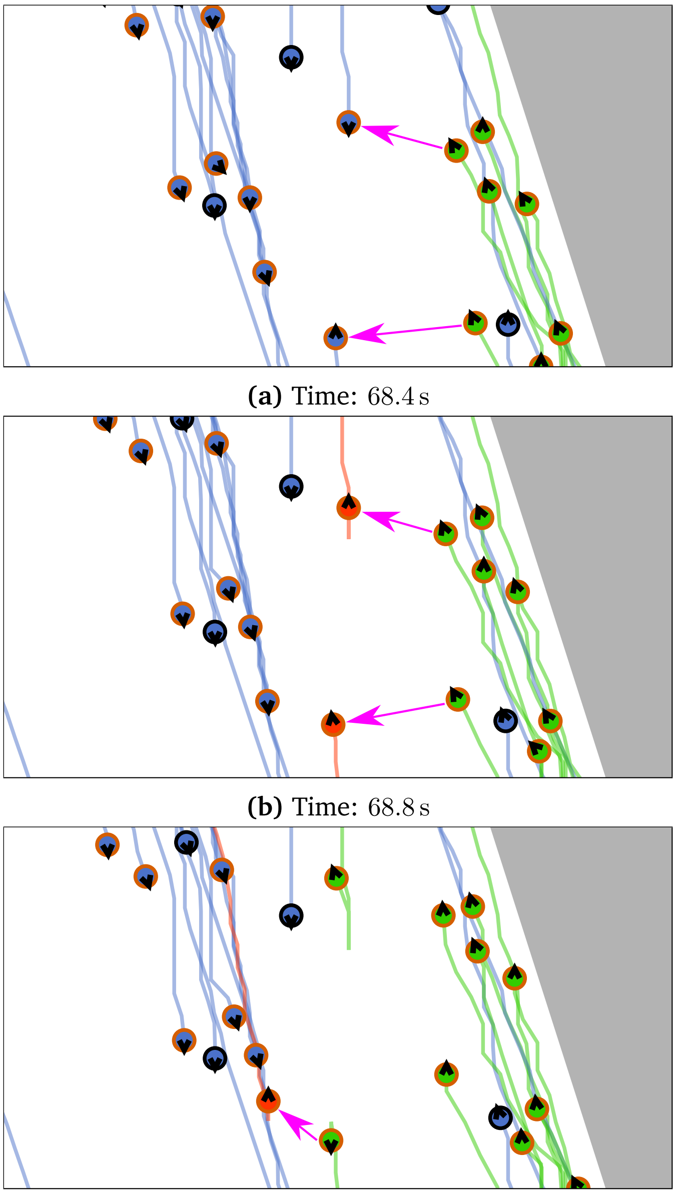
(b) Time: 61.6 s



(c) Time: 62.0 s

Figure 7.30: Magnified view of an agent which changes its behavior from escaping to "search for a safe zone" after leaving the immediate `Threat` radius. Red agents are still in the `Threat` radius, while the green agent indicates an agent searching for a safe zone. Small triangles indicate the walking direction of agents.

Magnified view: Imitation behavior of in-group members



(a) Time: 68.4 s

(b) Time: 68.8 s

(c) Time: 69.2 s

Figure 7.31: Imitation behavior of agents that did not perceive the threat themselves but perceive other escaping in-group members (brown encircled): **(a)** The target-oriented agent (blue) heading southwards perceives escaping agents (green) coming northwards. Another target-oriented agent (blue), which did not perceive the threat, is overtaken by escaping agents (green). **(b)** After processing the escaping agents in a cognitive phase, the in-group members feel threatened themselves (that is, they maximize the distance to the threat and search for a safe zone). **(c)** Another target-oriented agent feels threatened after perceiving an escaping in-group member and changes the walking direction towards its safe zone which is located southwards. Out-group members (black encircled) do not trust in others and strictly stick to their behavior (that is, being target-oriented).

Sensitivity study for the parameter "probabilityIngroupMembership" I conclude with a short parameter study which evaluates the effects of the newly introduced parameter `probabilityInGroupMemberhsip` on the evacuation time. To this end, I use the Vadere scenario from above and vary the parameter `probabilityIngroupMembership`. The parameter `probabilityIngroupMembership` controls how many of the agents are `IN_GROUP` members. `IN_GROUP` members trust each other and imitate each other, see Fig. 7.31, p. 134. We can hypothesize that an increasing number of `IN_GROUP` members leads to more imitating behavior which could lower the evacuation time of all agents. The evacuation time is the time until the last agent reaches a safe zone after the threat occurred at time step $60\,\mathrm{s}$. Surely, the evacuation time depends on what behavior is copied by `IN_GROUP` members. If many people are running, then people copying them lead to a fast evacuation. This observed behavior could be derived from the scenario description on p. 116 where many people were running because of the threat and this behavior was copied.

The parameter `probabilityIngroupMembership` is varied in the interval $[0.0, 1.0]$ in 0.1 steps. For each value, 30 simulations are conducted. Vadere's random seed feature is used for each simulation which ensures that the agents start at random positions inside the sources and the agents start with random preferred velocities drawn from a truncated normal distribution which is described in Tab. 7.7. Both parameter settings ensure randomness in the simulation.

Parameter name	**Value**
speedDistributionMean	1.34
speedDistributionStandardDeviation	0.26
minimumSpeed	0.50
maximumSpeed	2.20

Table 7.7: The speed configuration of agents in Vadere.

The plots Fig. 7.32 (p. 136) and Fig. 7.33 (p. 137) visualize the simulation results for 30 repetitions per parameter value using different statistical plots. Fig. 7.32 visualizes the distribution of the evacuation time as box plot with a focus on the minimum time, first quartile, median, third quartile, and the maximum time. The same data is visualized as violin plot in Fig. 7.33a to emphasize the skewness of the evacuation times for a parameter value to visually check if the data is normally distributed. The check for a normal distribution is important for a subsequent Student's t-test which requires normally distributed data. For the t-test, the 30 repetitions are interpreted as one single group. Then, I compare groups of different parameter values pairwise to check if the groups significantly differ from each other statistically, see Fig. 7.33b. The simulation results are also plotted as scatter plot in 7.33c which shows a relationship between the parameter `probabilityInGroupMemberhsip` and the evacuation time. The linear regression line in 7.33c shows a clear trend of decreasing evacuation time if agents trust each other (that is, a high `probabilityInGroupMemberhsip`). Of course, simulations only show one possible outcome of a scenario and not the ground truth. Random effects determine the trajectories of agents significantly which can cause that some agents imitate behavior but others do not. Nevertheless, the data suggests that a high probabilityInGroupMemberhsip leads to decreasing evacuation times. This is an important outcome for event practitioners and safety concepts for crowd events.

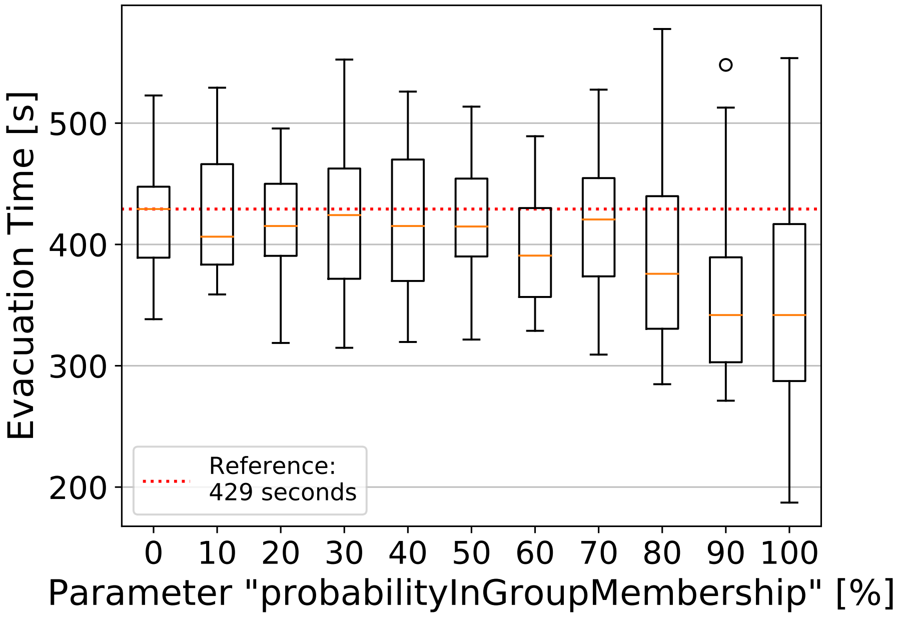
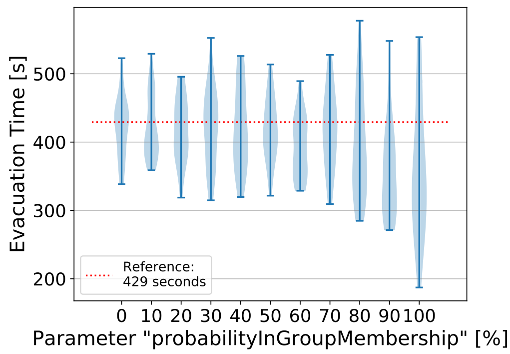
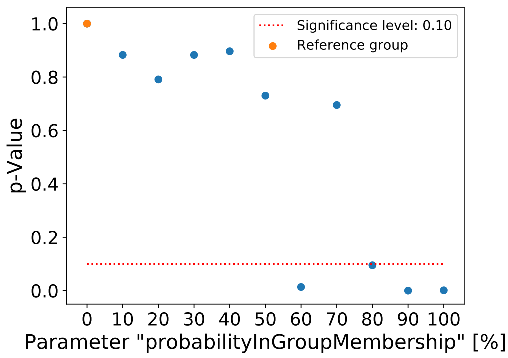


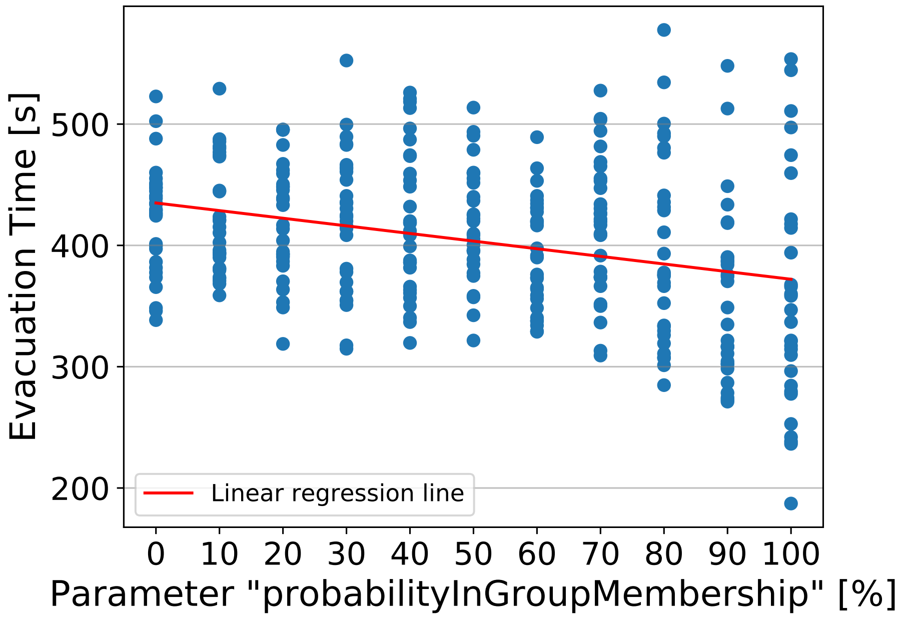
Figure 7.32: The evacuation time of all agents when varying the parameter probabilityIn groupMembership from 0 to 100%. For each parameter value, 30 simulations are conducted. The box plots highlight the median for the 30 repetitions and show a clear trend of a decreasing evacuation time if agents trust each other, that is, when probabilityIngroupMembership is high.



(a) Violin plot



(b) P-values for a pairwise t-test with the reference group (0%) and the null hypothesis that both groups have identical average values.



(c) Linear regression line

Figure 7.33: The 30 repetitions per `probabilityInGroupMembership` as different statistical plots: **(a)** As violin plot to highlight the skewness in each group. **(b)** The p-values as result of a pairwise t-test with the reference group (`probabilityInGroupMembership` = 0%) under the null hypothesis that both groups share the same mean. **(c)** As scatter plot (x-axis: `probabilityInGroupMembership`, y-axis: evacuation time) with a linear regression line (R2 score: 0.095, p-value: $\ll 0.001$) which shows a negative correlation (r-value: -0.308) between `probabilityInGroupMembership` and the evacuation time. That is, a significant tendency of decreasing evacuation time.

Model limitations The simulation results show that the model for behavioral changes is able to reenact the observed behavior after the false alarm at underground station Oxford Circus at least qualitatively. But of course, the model is a simplification in regard to psychological influences and also from a locomotion point of view.

In the simulation, agents use the whole width of the streets instead of using only the pavements. While this is plausible after the bang, it is certainly not realistic before the bang where pedestrians would use the pavements instead of using roads that are primarily intended for car traffic.

The simulation does also not contain advanced psychological aspects like helping behavior, where people help each other when being injured. Drury, Cocking, and Reicher 2009b showed that survivors of an emergency helped each other. This helping behavior was already simulated by modelers like Sivers, Templeton, et al. 2016. Additionally, psychologists stress that in-group members allow closer proximity to each other (Novelli, Drury, and Reicher 2010; Templeton, Drury, and Philippides 2018). The psychologists Templeton and Neville also stress the three transformations that are important to accurately describe crowd dynamics in regard of the social identity approach (Templeton and Neville 2020a, p. 63):

- Cognitive transformation: from personal identity to social identity (e.g., from father to football supporter).
- Relational transformation: one "other" becomes "one of us" (the crowd).
- Emotional transformation: for instance, positive emotions like empowerment when achieving a group goal

Furthermore, latest psychological researches suggest to additionally take the social appraisal theory into account when explaining collective behavior (Bruder, Fischer, and Manstead 2014). The social appraisal theory tries to explain how own emotions are influenced by the appraisal of others' emotions. The authors improve the primitive emotional contagion theory which suggests that a sender expresses an emotion and the receivers automatically mimic the expression shown by the sender (Bruder, Fischer, and Manstead 2014, p. 142). Social appraisal can be seen as mediation process: instead of just mimicking the sender's emotions and behavior, the receiver's behavior slowly converges to the one of the sender. The process is mediated by what psychologists call social appraisal. My implementation neglects such a meditation process for the sake of simplicity. The social appraisal theory would require to include emotional variables that would lead to a more complex model which would be similar to an eBDI approach (emotional beliefs desires intention).

These are all psychological implications. In the application, I have neglected the emotional aspects when modeling behavioral changes in favor of a minimal and reusable software structure because I did not need it. My primary goal is to establish a clean and reusable software architecture. When an application demands it, this minimal architecture can be extended by further psychological processes. The inclusion of all these additional processes which influence behavior is left to other modelers.

In the simulation, agents sharing the in-group membership, trust each other and imitate their behavior. This was achieved by adding a `SelfCategory` and a `GroupMembership` to agents. This can clearly be seen as social identification process — a cognitive and relational transformation from single, selfishly acting agents to a psychological crowd. It is a step forward to more realistic "social" simulations which also include psychological aspects. My modeling approach is a step towards psychologists and their demand that "social identification is a core component that influences the microscopic level factors in pedestrian movement" (Templeton and Neville 2020a, p. 71) which should be integrated into simulation models.

I decided to only include the essential aspects into my model so that it remains reusable and falsifiable and that scientific conclusions can be drawn from the model. The model is a starting point to test also psychological hypotheses and how they affect the evacuation time in emergencies. Such computer models and the subsequent simulations help to enhance the safety concepts for public places. This is particularly important in the UK where the high terrorism threat level leads to uncertainty in the population and causes false alarms with subsequent "collective flight incidents". These incidents are dangerous for people. The Oxford Street incident left nine people injured and even more psychologically distressed (Greenfield, Cobain, and Dodd 2017). My new model allows to scrutinize "collective flight incidents" in more details and helps to answer following questions:

- When and how do people perceive a signal as threatening?
- When and how do people flee?
- When do they follow (or ignore) others?
- What is the role of other groups (authorities, emergency services) in communicating information about threat?
- When do these responses become disorderly?

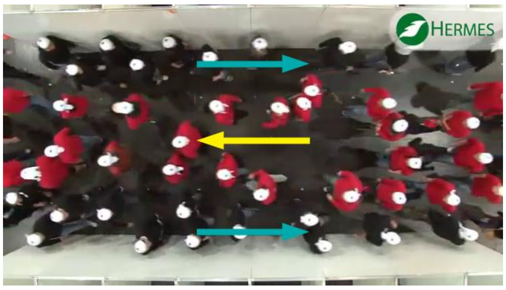
These questions are also raised by different researchers of the University of Sussex, Universities of St Andrews (Edinburgh), Lund University and Keele University. In a current research proposal, their goal is to develop a new psychological "model of 'stampedes' in response to perceived threats, based on a novel combination of social appraisal theory and the social identity approach" (Drury 2020, p. 1).

7.3 Use case 3 — Fictitious scenario: Counterflowing agents and evasion

This use case represents a fictitious scenario in a narrow corridor with counterflowing agents. Even if it is a fictitious scenario, the constellation with counterflowing pedestrian streams can often be observed in the real world. For instance, in pedestrian zones or supermarkets where space is limited. While the first two scenarios used the optimal steps model on the locomotion layer, this last scenario uses the experimental behavioral heuristics model to show that the software architecture is generic enough to be combined with different locomotion models and simulation tools. The behavioral heuristics model was introduced by Seitz in his dissertation (Seitz 2016). In it's current form, it can only be used for simple geometries and must be seen as an experimental model which is not widely adopted. My simulation results are not analyzed in depth as done with the previous simulations. Instead, the results are just validated qualitatively against behavior extracted from pedestrian experiments to show that this implementation is able to reenact real-world behavior.

7.3.1 Scenario description

A self-organization phenomenon called lane formation is often reported when observing bidirectional pedestrian flows. Lane formation means the phenomenon in crowds that opposite pedestrian flows tend to separate. In that case, pedestrians follow other pedestrians in the same direction very closely, see Fig. 7.34. Lane formation was studied and confirmed in older but also newer experiments by several authors (Muramatsu, Irie, and Nagatani 1999; Kretz, Grünebohm, Kaufman, et al. 2006; Ma et al. 2010; Feliciani and Nishinari 2016b). For instance (Kretz, Grünebohm, Kaufman, et al. 2006) reported the formation of two and three lanes during their experiment in a $34\,\mathrm{m} \times 2\,\mathrm{m}$ corridor (length $\times$ width) with 67 participants using different fractions of counterflow ([0.00, 0.10, 0.34, 0.50, 0.66, 0.90]).



(a) Source: Zhang, Klingsch, and Seyfried 2012, p. 6 (I added arrows to denote the walking direction)

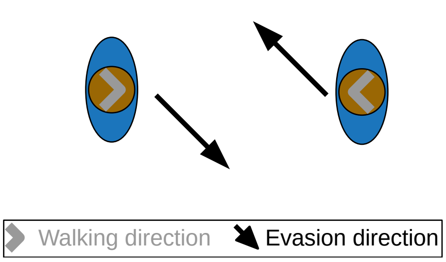
(b) Source: Kretz, Grünebohm, Kaufman, et al. 2006, p. 4 (I added arrows to denote the walking direction)

Figure 7.34: Lane formation as an emergent effect of counterflowing pedestrian streams was observed in several experimental setups in the past.

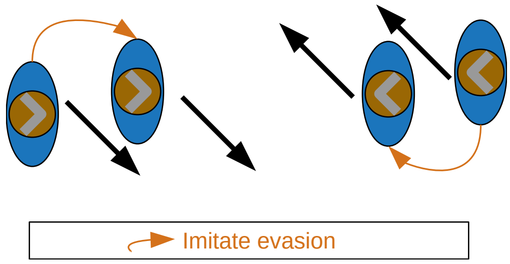
Several modelers were able to reproduce lane formation by only considering the physical locomotion aspect but neglecting cognitive aspects of counterflowing humans. For instance, Helbing and Molnár 1995 reported lane formation with their social force model or Liu et al. 2014 by using a model based on "utility optimization" to move agents similar to the optimal steps model. As stated in Sec. 7.1.1 (Fig. 7.1, p. 102), considering only physical aspects for agent navigation can lead to deadlock situations in simulations while real pedestrians keep moving.

7.3.2 Implementation details

As the preceding scenario description shows, pedestrians often form lanes in bidirectional traffic to maintain flow. Counterflowing pedestrians evade each other instead of strictly following their target direction. Based on the video footage from the "Pedestrian Dynamics Data Archive" (Boltes, Holl, and Seyfried 2020), I identified two simple heuristics which trigger the process of lane formation from the view of individual pedestrians: A pedestrian evades if **(1)** a neighboring agent occupies the current path but walks in a different direction or **(2)** the (neighboring) pedestrian in walking direction evades (that is, followers imitate the evasion behavior of the person in front of them), see Fig. 7.35.



(a) First cognitive heuristic: evaluate walking direction of opposite agent.



(b) Second cognitive heuristic: imitate evasion behavior if no counterflowing agent is present but agent in front evades.

Figure 7.35: Two simple heuristics to trigger evasion behavior of agents from a cognitive point of view.

These two heuristics are embedded into the generic psychology layer from Sec. 6.1 as following:

- Perception: nothing must be implemented because no environmental stimulus is necessary to achieve evasion behavior.
- Cognition: implement class `CounterflowCognitionModel` which varies agent's `SelfCategory` between `TARGET_ORIENTED` and `EVADE` by using the two heuristics from Fig. 7.35. Agents look for neighboring agents in a search radius r. If the neighboring agents walk in a different direction, change `SelfCategory` to `EVADE`. If the neighboring agent walks in the same direction and evades, imitate this evasion behavior.
  - The walking direction of an agent is derived from the floor field gradient which describes the shortest geodetic path to the agent's target. Fig. 7.36 visualizes how the walking direction is derived by using the floor field gradient.

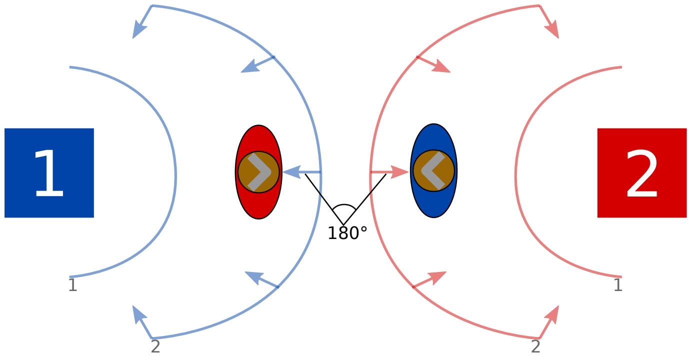


Figure 7.36: The walking direction of agents is derived by using the corresponding floor field and its gradient. The blue agent walks to the blue target (1) on the left-hand side. The red agent walks to the red target (2) on the right-hand-side. The curved lines denote the contour lines of the corresponding target floor field (gray numbers show the value of the contour line). Arrows denote the gradient of the floor field at that position (the shortest path to the target).

  - It is assumed that the walking direction of two agents differs if the angle between their walking direction vectors is greater than $45°$ (this is a configurable new attribute of an agent)

- Behavior: this time, the behavioral heuristics model (BHM) is used to move agents in the environment instead of the optimal steps model. The optimal steps model solves an optimization problem in each simulation step for each agent, see Sec. 2.2.3, p. 38. The BHM uses four strategies to move agents: **(1)** Step towards the target with step length d if this position is free. **(2)** If the position from step (1) is occupied, try to evade tangentially ($45°$). **(3)** If the tangential position is occupied, try to evade with a sidestep ($90°$). **(4)** If this position is also occupied, wait. The following three extensions are added to the original BHM:
  - The original BHM uses the Euclidean distance to derive the direction of an agent to its target. This imposes problems when an obstacle is located between an agent and its target. Then, the target direction would point into the obstacle and agents would be blocked. Therefore, a floor field, based on the eikonal equation, is generated to be able to derive the geodesic distance and geodesic direction of an agent to its target. The Vadere framework already provides methods to generate floor fields which can be used along with the BHM.
  - The method `PedestrianBHM.collideWithPedestrianOnPath()` does not take the future path of an agent into account even if the name would suggest it. Therefore, I extend this method to only take agents into account which are located on the path towards an agent's target.
  - The BHM searches a new agent position in the method `update()` of class `PedestrianBHM`. Now, this method takes the current cognitive status of an agent into account. If an agent has the status `EVADE`, the agent tries to evade tangentially or sideways by using the class `NavigationEvasion` temporarily, see List. 7.3.

Listing 7.3: The `update()` method of class `PedestrianBHM` which reacts to the current cognitive status in `agent.getSelfCategory()`.

```java
public void update(double currentTimeInSec) {
    ...
    SelfCategory selfCategory = getSelfCategory();
    VPoint position = getPosition();

    if (selfCategory == TARGET_ORIENTED) {
        // Use regular heuristics to move agent
        updateTargetDirection();
        nextPosition = navigation.getNavigationPosition();
        makeStep();
    } else if (selfCategory == EVADE) {
        // Evade tangentially or with sidestep
        INavigation evasionNavigation = new NavigationEvasion();
        evasionNavigation.initialize(this, topography, null);
        nextPosition = evasionNavigation.getNavigationPosition();
        makeStep();
    }
    ...
```

```
}
```

The UML activity diagram Fig. 7.37 summarizes the cognitive process of agents which is carried out in the `update()` method of class `CounterflowCognitionModel`.

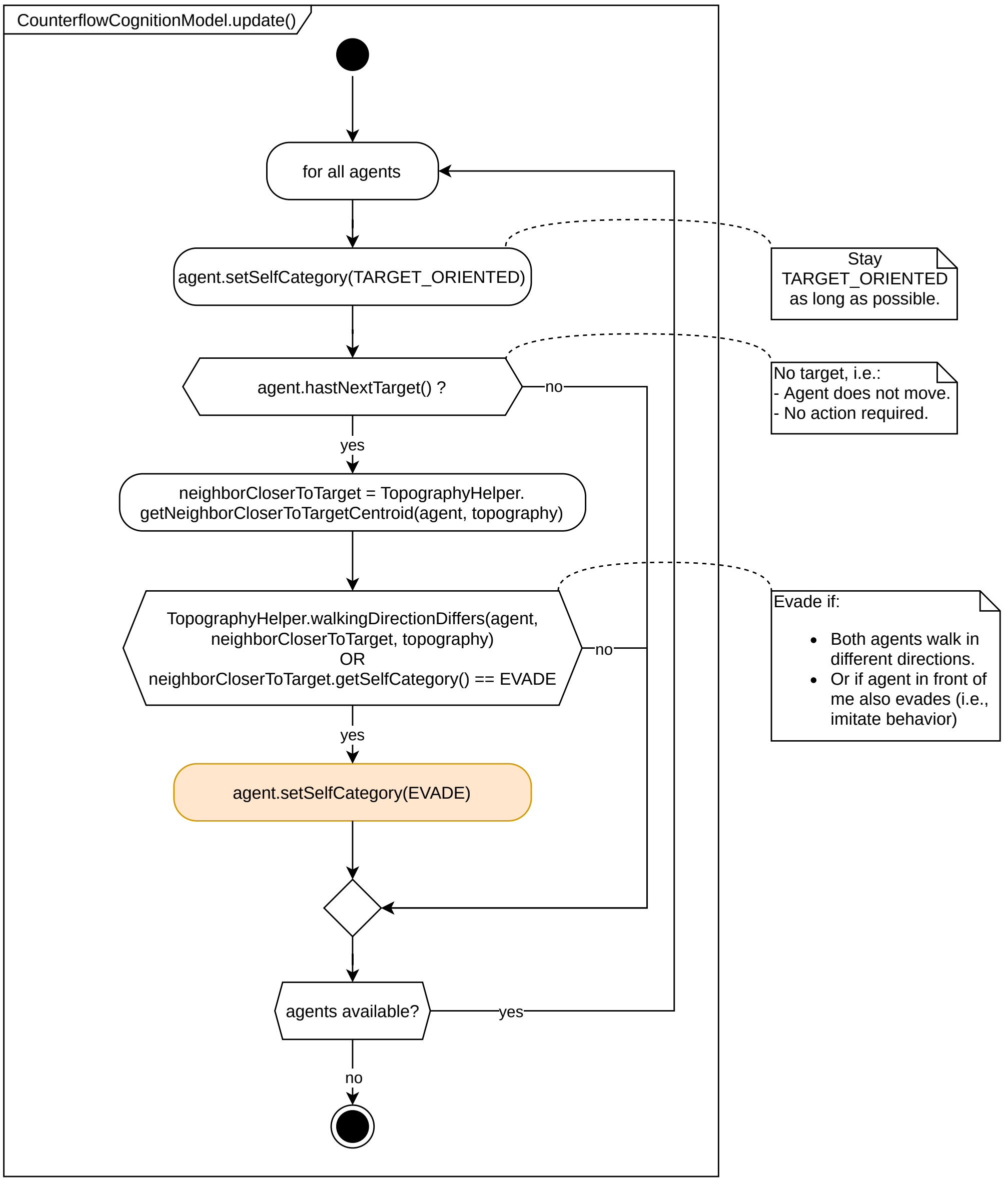


Figure 7.37: UML diagram of the `CounterflowCognitionModel`. Existing locomotion models like the social force model focus on target attraction and agent repulsion to achieve evasion behavior. But, a simple cognitive heuristic mimics human behavior more naturally: agents simply process two information and evade tangentially or sideways if one of these information holds true. **(1)** Does the next neighboring agent walk in different direction? **(2)** Does the neighboring agent evade?

The implementation is covered by unit tests which results in the code coverage in Tab. 7.8.

Class name	Total lines	Line coverage [%]	Branch coverage [%]
Note: no perception class required	-	-	-
`CounterflowCognitionModel.java`	14	93	90
`OSMBehaviorController.java`	96	54	50

Table 7.8: The code coverage for the newly introduced classes which are required for the third use case. The code coverage was obtained for Git commit `da89eafa` with the Java code coverage library "JaCoCo" version 0.8.3: `https://www.eclemma.org/jacoco/`

7.3.3 Simulation results and validation

Simulator version and scenario file

The simulations were carried out with Vadere version `1.15` (Git commit hash: `c2f7c07f50ce22dde6d7afbbff21ce6d842df92f`). The scenario file, which contains all simulation parameters, can be found as PDF attachment (click the icon to save file to disk):

I applied the model from the previous section in a topography with a narrow corridor of $19\,\mathrm{m} \times 1\,\mathrm{m}$ (length $\times$ width). 20 agents move from left to right and 20 agents move from right to left. On locomotion layer, default parameters are used for the behavioral heuristics model and agents use a search radius of $4\,\mathrm{m}$ to look for neighboring agents. When agents have `SelfCategory.EVADE` assigned, they either evade tangentially or with a sidestep as shown in List. 7.3 (line 11–17). The agents use only a subset of the available movement heuristics and omit the "step or wait" and "follower" heuristic. Qualitatively, we can clearly see that agents form two lanes after detecting the evasion situation in a cognitive process, see Fig. 7.38.

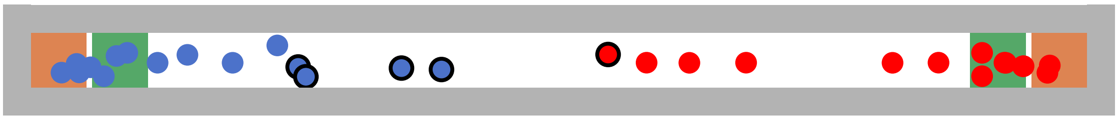
A closer look at the simulated trajectories reveals movement artifacts which are introduced by the behavioral heuristics locomotion model. Agents evade towards a wall and are immediately "bounced back" which leads to unrealistic zig-zag trajectories, see Fig. 7.39. This can be explained by the experimental status of the behavioral heuristics model. The focus of my work is to provide a generic architecture to allow behavioral changes of agents and not to refine an existing locomotion model. Therefore, I don't address the unrealistic zig-zag trajectories in my work. Instead, the simulation result shows that agents detect counterflowing agents in a cognitive process and change their `SelfCategory` from `TARGET_ORIENTED` to `EVADE`. In the locomotion phase, agents evade tangentially or with a sidestep.

7.4 Summary

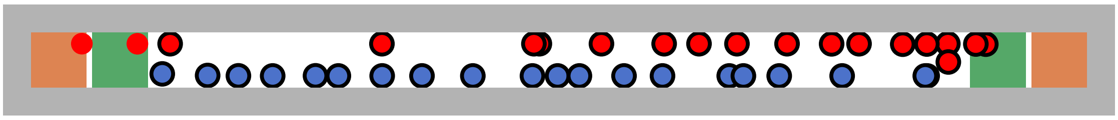
In this chapter, I used the new psychology layer from the previous Sec. 6 with sub-layers perception, cognition and behavior. I extended it with application-specific knowledge from three scenarios and validated the simulation results against real-world observations. I based this application-specific knowledge on three scenarios: **(1)** An own experiment with 58 participants which I conducted in Oct 2018 where a participant is asked

(a) Time: 0.0 s

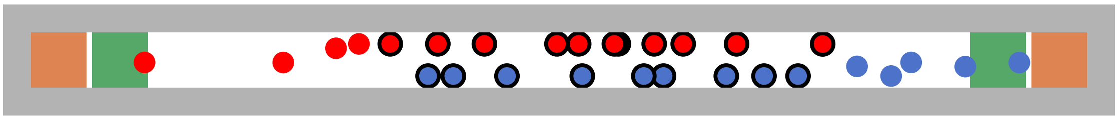
(b) Time: 4.0 s



(c) Time: 4.4 s



(d) Time: 12.0 s



(e) Time: 16.8 s

Figure 7.38: Behavioral changes of agents in the course of the simulation. Blue agents walk from left to right. Red agents walk from right to left. Agents with `SelfCategory.EVADE` are encircled in black. **(a)** and **(b)** Agents start walking in the green source areas. **(c)** The red agents change from `TARGET_ORIENTED` to `EVADE` after detecting a counterflowing (blue) agent in a cognitive process. Also the foremost (blue) agent detects a counterflowing agent which causes the blue agent to change the behavior. The following (blue) agents imitate this behavior. **(d)** and **(e)** The counterflowing agents form two lanes which are dissolved at the end of the simulation when agents turn back to `SelfCategory.TARGET_ORIENTED`.

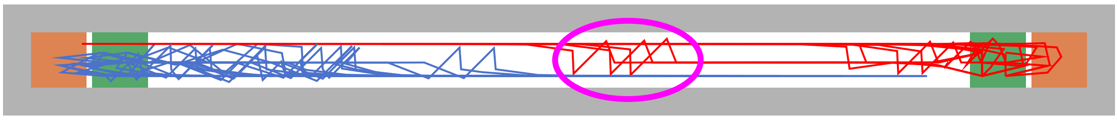


Figure 7.39: Movement artifacts of the experimental locomotion model: agents are bounced back from walls which leads to unrealistic zig-zag trajectories.

to cross a dense, waiting crowd. **(2)** A false alarm at underground station Oxford Circus (London, 2017). **(3)** A narrow corridor with two counterflowing pedestrian streams. The crucial aspect for the application-specific knowledge was to identify triggers on the cognitive level which cause humans to change their behavior. Three triggers where identified:

- For the experiment: a person realizes that he/she cannot move anymore when confronted with a waiting crowd. Then, the person changes the behavior from target-oriented to cooperative to be able to cross the waiting crowd.

- For the false alarm: a loud bang — an environmental stimulus — causes people to escape (they increase their walking speed and maximize the distance to the bang). Other, people who did not perceive the bang imitate the escaping behavior when perceiving fleeing people.
- For the narrow corridor: people change their behavior from target-oriented to evasion when they detect counterflowing pedestrians directly in front of them or when their neighbor (in same direction) evades, that is, they imitate behavior.

These triggers where implemented as implementations of the interface `ICognitionModel` from the psychology layer and can easily be enabled/disabled (List. 6.5, p. 98) when setting up a scenario in the Vadere simulator. The whole concept of the psychology layer provides a generic architecture to allow behavioral changes of agents in simulations. First, environmental stimuli are processed on the perception layer. Then, this information is enriched with other information — e. g., the triggers from above — in a cognitive process on the cognition layer. Lastly, according to the cognitive status an agent carries out a movement on locomotion layer. For developers, the psychology layer provides a clear framework to map human behavior onto a clean and reusable software architecture to reenact real-world observations accurately.

Chapter 8 Summary, conclusions and outlook

The last section briefly summarizes my work chapter by chapter, draws general conclusions and gives an outlook on future work.

8.1 Summary

The goal of this work was to model behavioral changes in agent-based simulations. I transformed this goal into a research question: how can changes in human behavior be operationalized for simulations? This revealed two key terms: behavioral changes and simulations. The key terms show that two different research disciplines are involved to find answers to the question: social sciences which cover humans, their behavior and behavioral changes. And natural sciences which help to derive mathematical and algorithmic models from real-world observations and to carry out computer simulations. For me as a computer scientist, the challenge was to bridge the gap between both worlds. I strove for a model and a reusable software architecture that covers a wide range of real-world scenarios and is therefore beneficial for the whole research community.

To this end, I subdivided this dissertation into two parts. The first part contains a broad literature research. The second part describes my modeling efforts to obtain a minimal and reusable software architecture that allows behavioral changes of agents.

I shed light on existing approaches to model and simulate pedestrian streams. I classified these approaches into macroscopic, mesoscopic (multi-scale) and microscopic pedestrian models and provided many examples for each model type. While macroscopic approaches do not distinguish individual agents, microscopic approaches strongly focus on individuals. This made microscopic models my choice to include psychological processes because previous researches revealed that crowd behavior is affected and generated by individuals. I evaluated seven open-source pedestrian stream simulators which implement locomotion models or subsets of them. With sustainability in mind, I decided to integrate my findings in an established open-source simulator. I chose Vadere which originally was designed as a framework to compare different locomotion models. Its clean architecture and the well-validated locomotion models helped to easily integrate my findings. Nevertheless, my modeling and architectural approach is not limited to the Vadere simulator. The approach could directly be adopted by other simulator developers and researchers.

In addition to locomotion modeling, I scrutinized psychological aspects in my literature research to model behavioral changes accurately. Psychology, as the scientific study of the behavior of individuals and their mental processes, helped to identify three key concepts which should be integrated into a pedestrian dynamics model: perception, cognition and a behavioral repertoire of agents. These three key concepts help to mimic what real humans do: they perceive their environment, process this input and adapt their behavior accordingly. I found that these three psychological key concepts are usually not implemented in current pedestrian stream simulation tools.

Human behavior is also affected by the social context. Therefore, I took a closer look at the social psychological perspective. This research revealed two further aspects which should be integrated into a model/architecture that allows behavioral changes of agents: social identities and self-categorization. The term social identities describes that humans have multiple identities when taking part in social life with others. The process of self-categorization describes the shift from one identity (category) to another one. That is, humans categorize themselves into categories (identities) to which they belong to when coming together in a social context. Then, they apply the norms of this category. For a simulation model this means that agents must be equipped with a self category which can change in the course of a simulation as consequence of environmental stimuli and cognitive processing of the close neighborhood. In this work, I chose to label the agents' self categories with the (expected) behavior on the locomotive level, e. g., target-oriented or cooperative.

In the second part of this work, I derived a reusable software architecture which can easily be employed in a wide range of pedestrian simulators. My architecture represents a simple psychology layer with the three sub-layers: perception, cognition and a behavioral repertoire, see Fig. 8.1, p. 149. The psychology layer is optional and can be enabled/disabled for each simulation run. This layered software structure, complemented by suitable algorithms, operationalizes changes in human behavior for simulations. Therefore, my contribution is one possible answer to the former research question of "How can changes in human behavior be operationalized for simulations?"

In a test-driven development process, I verified my implementation with several unit tests. A carefully configured continuous integration pipeline executes the unit tests upon each source code change and deploys the Vadere simulator along with my new model to the Vadere website.

In a validation phase, I ensured that my model is able to reenact real-world observations accurately. I selected three real-world use cases: **(1)** An own experiment where a walking participant crosses a dense, waiting crowd. **(2)** An incident in London's Oxford Street where a perceived threat caused thousands of pedestrians to change their behavior from shopping to escaping and members of a shared social category (identity) follow each other. **(3)** A scenario in a narrow corridor with counterflowing pedestrians. The three use cases helped to identify triggers on the cognitive level that cause a behavioral change and to complete the generic psychology layer with application-specific knowledge. Now, **(1)** agents are able to act in target-oriented way like commuters, **(2)** they can act cooperatively as observed in dense crowds and **(3)** agents can react to environmental stimuli and their direct neighbors (the social context) which can lead to behavioral changes.

A picture in the summary seems uncommon, but it conveys my take-away message of this dissertation very concisely: integrating psychological aspects into existing pedestrian simulators makes simulations more realistic and by using my layered approach it comes with little implementation overhead. Therefore, instead of wasting valuable resources on software development, crowd modelers can concentrate their effort on the important part: the model. The left listing in Fig. 8.1 shows how a simulation loop employs the new psychology layer. The right image in Fig. 8.1 visualizes the three sequential steps of the psychology layer: perception, cognition and a behavioral selection.

```
while (simulationIsRunning) {
  ...
  // Perception
  perceptionModel.update(agents,
    stimuli);
  ...
  // Cognition
  cognitionModel.update(agents);
  ...
  // Locomotion
  locomotionModel.update(agents,
    time);
  ...
  time++;
}
```

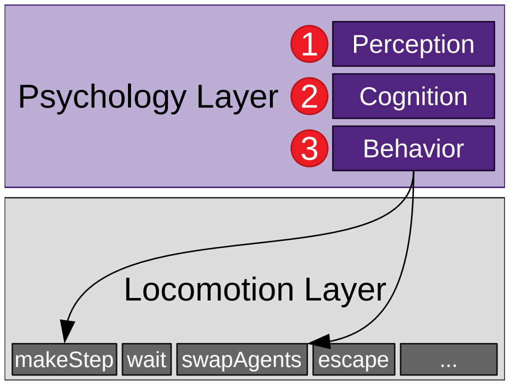


Figure 8.1: Minimal modeling effort to integrate central psychological aspects in established pedestrian stream simulators (original listing and image: p. 91).

8.2 Conclusions

In my overview of the state of the art, I worked out that the current modeling approaches for pedestrian dynamics focus too much on physically correct simulations: agents walk from sources to targets while avoiding obstacles and other agents. Of course, this assumption is a good starting point for pedestrian simulations but realistic models should not stop here. It limits crowd simulations mostly to evacuation scenarios where evacuees permanently stick to a single behavior — being target-oriented. This simple approach fails in situations which seem only slightly different. Other modeling approaches include certain psychological aspects but are tailored to one very specific scenario only. Thus, these psychologically-inspired models are not reusable. I addressed this problem by introducing a well-defined psychology layer with sub-layers perception, cognition and a repertoire of behaviors for agents. This approach allows agents to change their behavior in the course of a simulation and makes simulations more versatile. For example, agents can change their behavior from being target-oriented to being cooperative and can swap places with other cooperative agents. Practitioners can now use such simulations to estimate how long it takes for a first responder to reach an injured person in a crowded scene. Or, law enforcement forces can use simulations to measure how long it takes to evacuate a crowded scene after a threat; in both cases, when people trust each other and when they do not trust each other. Former modeling approaches were not able to replicate such real-world observations in a reusable way.

I see four benefits of my work:

- Two improvements on the modeling:
    1. My psychology layer is based on empirical data. I conducted an own experiment with 58 participants to observe and document changes in human behavior.
    2. Together with social psychologists, I used the experiment data to operationalize the process of behavioral changes into three sequential phases: perception, cognition and a selection of appropriate behaviors.
- Two improvements on the software reusability:
    3. I encapsulated the three phases into a clean and simple psychology layer. I integrated it into Vadere, carried out simulations and validated the model successfully. This shows clearly that my model is very close to real applications and not another vague and not falsifiable model of human behavior and behavioral changes.
    4. I designed the psychology layer as reusable approach which can easily be integrated in other crowd simulation tools. This makes my model sustainable and beneficial for the whole pedestrian dynamics research community.

I implemented this new psychology layer in the open-source pedestrian simulator Vadere. It was originally designed as framework to compare different locomotion models. I drew upon on this framework idea. My goal was to push this idea further to a framework that also allows to test psychological hypotheses about perception, cognition and behavior. However, my approach is not limited to the Vadere simulator. The generic idea of extending the simulation loop by a perceptional and a cognitive phase which influence the behavioral selection of agents can easily be integrated into other microscopic pedestrian simulation tools. My generic psychology layer

1. provides a clear guideline on how to operationalize observed behavior for computer models — even for non-psychology experts —, and
2. is reusable for a wide range of real-world scenarios as the validation with three use cases showed.

I used the three-step process perception, cognition and a behavioral selection because it can be easily understood by researchers from different disciplines. It is well-grounded in the psychological world but also natural scientists are able to understand the concept and complement it with application-specific knowledge. My modeling approach is a step forward: it establishes the required connection between life and natural scientists. For realistic simulations and to better understand crowd behavior, knowledge from both disciplines is necessary and both disciplines can and should benefit from each other. By fostering understanding and following this synergistic relation, my work helps to make crowd gatherings safer.

I believe that my psychology-related modeling is just the starting point for more evolved models and more validation. Natural and life scientists should work closer together to obtain more realistic models. I hope that more modelers integrate (basic) psychological findings in their models without making the model too complex.

8.3 Outlook

In my dissertation, I integrated my findings in the Vadere simulation framework. As every software project, Vadere can be continuously improved. Outdated and unused code should be removed to keep the architecture clean and maintainable — which is a continuous effort. A code quality tool like SonarQube can help to identify code smells. One important issue to solve is to make the GUI more user-friendly that non-experts can set up simulation scenarios. One architectural decision which could be made here is to offer Vadere as a web service. This requires that Vadere's simulation loop runs on a web server and is complemented by a HTML/CSS/JavaScript GUI. This is a major redesign but could make Vadere accessible for non-experts because tablets and smartphones could be used to access pedestrian simulations. Another important topic is to accelerate the simulations. Large scenarios ($1000\,\mathrm{m} \times 1000\,\mathrm{m}$ and bigger) with thousands of agents take hours to compute. It would be beneficial to shorten this computation time.

From a modeling perspective, one could explicitly introduce social identities and norms instead of the more general (social) categories which I employed. My introduced (social) categories like target-oriented and cooperative give a clear hint what is expected on the locomotion layer and makes my approach reusable for a wide range of real-world scenarios. Nevertheless, from a social psychological perspective it is a simplification. Introducing identities and norms could make the behavioral selection more granular. For example, target-oriented football supporters (first identity) could keep a closer proximity to each other than target-oriented fathers (second identity).

So far, I have shown the versatility of my new modeling approach by using three real-world scenarios. It would be beneficial to operationalize and simulate more observations from real life. Applying a model helps to detect shortcomings and to develop model refinements.

I would like to close with a final remark on crowd simulations: all simulation results must be treated with care because crowd behavior is very hard to predict. On the one hand, simulations can help to detect risks when crowds gather. On the other hand, simulations cannot ensure that all risks for life and limb are found.

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Appendix

1 Obtain lines of code (LOCs) for different simulators

The lines of code exclude unit tests, blank lines and comments. The "cloc" software tool[1] version 1.74 was used to obtain the lines of code. The hash contained in the `-report-file` indicates the analyzed simulator version according to the Git version control system.

Listing 1: The "cloc" software was used to obtain the lines of code for different simulators excluding unit tests, blank lines and comments.

```
FDS+Evac:
cloc
--report-file=fds-5c0149698-cloc_report.txt
.

GAMA:
cloc
--report-file=gama-d81fcb858-cloc_report.txt
.

JuPedSim:
cloc
--exclude-dir=Utest
--exclude-lang=XML
--report-file=jupedsim-d942c947-cloc_report.txt
jpscore/ jpseditor/ jpsreport/ jpsvis/
.
Menge:
cloc
--match-d=src
--exclude_dir=test
--report-file=menge-menge-c3eb429-cloc_report.txt
.
MomenTUMv2:
cloc
--exclude-dir=momentum-documentation,tests
--exclude-lang=HTML,CSS,XML
--report-file=momentumv2-55c8f3a-cloc_report.txt
.
SUMO:
cloc
--match-d=src
--report-file=sumo-1.0.1-cloc_report.txt
.
```

[1] https://github.com/AlDanial/cloc

```
Vadere:
cloc
--exclude-dir=tests
--exclude-lang=JSON --report-file=vadere-87b4fe32-cloc_report.txt
.
```

2 Clean code exemplified by the class "CooperativeCognitionModel"

Clean code is obtained by several measures: **(1)** a minimal documentation of the purpose of a class, **(2)** short methods with well-defined interfaces and **(3)** descriptive variable and method names.

Listing 2: Clean code exemplified by the class `CooperativeCognitionModel`

```java
package org.vadere.simulator.control.psychology.cognition.models;

/**
 * The {@link CooperativeCognitionModel} makes a pedestrian cooperative
   if its
 * average speed falls below a certain threshold. I.e., usually the agent
 * could not move for some time steps. For example, in case of other
 * counter-flowing agents.
 *
 * {@link SelfCategory#COOPERATIVE} should motivate pedestrians to swap
   places
 * instead of blindly walking to a target and colliding with other
   pedestrians.
 */
public class CooperativeCognitionModel implements ICognitionModel {

    private Topography topography;

    public void initialize(Topography topography) {
        this.topography = topography;
    }

    public void update(Collection<Pedestrian> pedestrians) {
        for (Pedestrian pedestrian : pedestrians) {
            if (pedestrianCannotMove(pedestrian)) {
                pedestrian.setSelfCategory(SelfCategory.COOPERATIVE);
            } else {
                pedestrian.setSelfCategory(SelfCategory.TARGET_ORIENTED);
            }
        }
    }

    private boolean pedestrianCannotMove(Pedestrian pedestrian) {
        boolean cannotMove = false;

        FootstepHistory footstepHistory = pedestrian.getFootstepHistory()
    ;
        int requiredFootSteps = 2;

        if (footstepHistory.size() >= requiredFootSteps
```

```
                && footstepHistory.getAverageSpeedInMeterPerSecond() <=
    0.05) {
            cannotMove = true;
        }

        return cannotMove;
    }
}
```